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Taking the Aid Debate to the Sub-National Level: Impact and Allocation of Foreign Health Aid in Malawi

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Abstract— I examine the allocation and impact of foreign health aid at the sub-national level in Malawi. The literature remains divided over the impacts of health aid— some scholars fail to find significant relations between health aid and health outcomes, while others praise notable impacts. Moreover, the approaches scholars use to examine impacts are as polarized as their results— aid impacts are primarily examined using cross-national analyses or at the project level. However, the emergence of geocoded aid data allows for a new analytical approach, one of examining aggregate health aid within a country. I use an AIC-based hierarchical model averaging approach to determine the best predictor variables of health aid in four time periods, examining how health aid is allocated according to socio-economic factors, health conditions, and ethnic preferencing. In addition, I use propensity score matching methods to examine the causal impacts of health aid. Results show that aid is generally not allocated to the poorest individuals, but results are mixed over allocation according to health conditions. In addition, only one year, 2010, shows evidence of possible ethnic preferencing influencing aid allocation. Despite mixed results of allocation, propensity score matching methods show health aid causing statistically significant improvements in health conditions in 2008, 2009, and 2010, causing a reduction of 0.3 to 5 million cases of illness annually. Results highlight notable aggregate health aid impacts, despite potential inefficiencies or negative consequences of aid.

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I. INTRODUCTION

Easterly opposed bednet distribution. [The World Bank] rejected Easterly's advice, and cut malaria sharply. Yes, debate's over. Aid works!

—Jeffrey Sachs, 2014

The big aid debate that Sachs initiated is now really over… His idea that aid could achieve rapid development and the end of poverty was wrong, and it's time to move on.

—William Easterly, 2013

In the past twenty years, foreign health aid has quintupled, increasing from $5.7 billion in 1990 to $26.9 billion in 2010 (Butler 2011). The growing commitment to address health challenges abroad has been matched by scholars seeking to evaluate these well-intentioned efforts. However, the current literature is riddled with contrasting results rather than consensus as to whether health aid works or not (despite scholars on both sides of the debate claiming that 'the debate is over') (Easterly 2013; Murphy 2014; Sachs 2014). Some find claims of foreign health aid effectiveness to stop at rhetoric, failing to find significant empirical relationships between health aid and improved health outcomes (Williamson 2008; Gebhard et al 2008; Wilson 2011; Kizhakethalackal 2009). Others empirically show notable impacts of health aid, praising impacts and urging donors to increase funding (Demombynes and Trommlerova 2012; Fegan et al 2007; Sachs 2014; Mishra and Newhouse 2007; Feeny and Ouattara 2013).

As polarized as the results are the approaches scholars use to examine aid impacts, with certain analyses leading towards certain results. Macro-level analyses that use the country as the unit of analysis and ask whether aid causes aggregate health outcomes to improve largely show health aid to be ineffective or minimally effective. The most promising results of health aid have come from project-level evaluations, where scholars have analyzed the impact of specific health interventions. Contrasting results have fueled the aid debate, but also have caused scholars to ask why aid may be successful at the project level while aggregate aid may be "less the sum of its parts." In particular, some scholars argue that potential negative consequences of aid wash out aggregate impacts (Howes, Otor, and Rogers 2011). In this paper I examine health aid from a middle ground, broadening the unit of analysis from the project-level and narrowing the unit of analysis from the macro-level. Specifically, I examine health aid at the sub-national level, examining the aggregate impact of all health aid projects within a country. The emergence of geographically referenced aid information makes this type of analysis possible.

Sub-national aid data offers a new lens to view foreign aid, allowing old questions to be asked in different ways, and entirely new questions to be asked altogether. As opposed to project-level analyses, cumulative impacts of aid can be examined to better understand its aggregate impact in a country. This is especially important in light of scholars arguing that negative impacts of aggregate aid could make its overall impact insignificant. Additionally, as opposed to asking if aid improves country-level health indicators, questions of aid effectiveness can ask where aid was allocated within a country and if individuals in those specific areas benefited. To date, no peer-reviewed study has examined the impact of aggregate health aid at the sub-national level. This paper fills that gap.

I examine the allocation and impact of foreign health in Malawi at the sub-national level. Malawi is chosen because it has the first fully geocoded dataset of reported aid projects, which was developed by the Malawi Ministry of Finance in partnership with the AidData Center for Development Policy. However, Malawi provides an ideal case study due to reasons beyond data availability. Malawi remains one of the poorest countries in the world, facing among the highest rates of disease burdens. Over 90% of the population lives on less than 2 dollars a day, and the United Nations Development Index ranked Malawi 171 out of 187 countries (UNDP 2010; Wroe 2012). Additionally, Malawi faces the ninth highest HIV prevalence in the world, and malaria accounts for 34% of all outpatient clinical visits ("Department for International Development: Aid to Malawi" 2009; Presidents Malaria Initiative 2014). With poor conditions, Malawi has received above-average amounts of per-capita development assistance. In 2010, out of the forty-eight countries in sub-Saharan Africa, Malawi received the 25th highest per capita amounts of foreign aid, $16.5 higher than the average in sub-Saharan Africa (World Bank 2014). Poor conditions and high amounts of aid suggest that foreign aid could have a significant ‘bang for its buck.’ However, a number of cases of corruption have caused donors to express concern about aid effectiveness, and in some instances have caused them to cancel aid contracts. Therefore, examining aid effectiveness within Malawi itself is particularly warranted.

This paper asks two main questions. First, I ask how aid is allocated. I examine how health aid relates to a number of factors that measure ‘need,’ including a variety of socio-economic and health variables. Additionally, I examine the importance of political factors driving allocation, specifically examining whether aid is more likely to go to individuals that are of the same ethnic group as the president (here, Bingu wa Mutharika). Second, I ask what impact (if any) health aid has on health conditions. Further insight comes from combing results of the two questions, asking how allocation might influence aid effectiveness.

The paper is organized as follows. First, I overview the literature relating to the allocation and impact of aid. Second, I place the analysis in its country-specific context by examining both the health conditions and history of foreign aid to Malawi. Third, I describe the data and present how each variable could affect aid allocation and health conditions. Fourth, I examine the allocation of foreign health aid, asking how aid responds to socio-economic, health, and political variables. Fifth, I examine the determinants of health outcomes, asking how important health aid is compared to other variables and gaining initial insights into health aid impacts. Sixth, I examine the causal impact of health aid. Discussion and conclusions follow.

2. AID ALLOCATION AND IMPACT

2.1 Allocation of Foreign Aid

From an aid-effectiveness perspective it is not sufficient to look at countries only, because countries often include a wide variety of different regions with different characteristics and degrees of need… Despite its importance for aid effectiveness, the distribution of aid across sub-national regions receives very little attention in both development theory and practice.

—Elena Pietschmann, 2014

Studies examining the allocation of aid have historically focused on the cross-national level, using individual countries as the unit of analysis. Alesina and Dollar (2000) find that both need and political factors, including colonial past and political alliances, drive aid allocation. Dollar and Levin (2004) confirm that both poverty and political factors drive allocation; however, institutions and political factors have only become important for aid allocation in the past couple decades. Scholars have also highlighted differences in how countries allocate aid. For example, China, like many countries, allocates according to political considerations, whereas institutional factors, such as democracy and governance, are not important (Dreher and Fuchs 2011). In contrast, Nordic countries particularly respond to openness and good institutions (Alesina and Dollar 2000). The United States preferences counter-terrorism and the Middle East peace process in allocating aid (Bortolleto 2011), while France preferences its former colonies (Alesina and Dollar 2000).

While cross-national analysis offers insights into political motivations for allocating aid, it is limiting in explaining whether aid is given to individuals most in need (Powell and Findley 2011; Pietschmann 2014). For example, while literature offers that donors generally give funding to countries with high need, it offers no insight as to whether funds go to the poorest regions or people within that country. Additionally, while the literature shows that political factors influence which countries receive aid, it says nothing about how political factors influence aid allocation at the country-level. Therefore, sub-national analysis offers unique insight into whether aid is effectively allocated within a country (Glassman 2014; Pietshmann 2014).

While at the cross-national level donors drive aid allocation, at the sub-national level both donors and recipient governments influence where aid is allocated. Jablonski (2014) notes that, “[i]n nearly all but the most unstable political environments, donors cooperate with government agencies in order to allocate aid.” Donor-recipient cooperation stems from the 2005 Paris Declaration on Aid Effectiveness, which emphasizes reliance on, “local government institutions for the provision of development services when possible” (Jablonski 2014). In addition, the type of aid can influence the control over funds. Aid in the form of budgetary support is entirely at the discretion of government ministries, whereas aid towards particular development projects will see more donor-recipient cooperation in deciding how much funding to give and where aid should be directed. However, donors often delegate responsibility of aid management because recipient governments have greater information on how to best allocate aid (Jablonski 2014; "Financial Management in Action," 2010).

Sub-national analysis of foreign aid has largely been a neglected topic. Donors themselves scarcely mention sub-national allocations. Higgins, Bird, and Harris (2010) reviews policy documents from major donors and finds that only one agency, the Australian Agency for International Development, addresses the issue of sub-national disparities. Pietschmann (2014) argues that this "suggests that regional inequalities are not a policy priority for donors." However, a literature examining the sub-national allocation of aid has begun to emerge with the growing availability of geocoded aid data (Pietschmann 2014). The creation of such data has been driven in part by a demand for greater transparency of aid flows (Chandy et al 2013).

Sub-national analysis has brought light to potential inefficiencies of aid allocation. Chandy et al (2013) examine whether foreign aid is allocated to the poorest regions within a country by combining data from the World Bank's "Mapping for Results" initiative and country-level poverty data. In examining twenty-four countries that collectively contain 359 aid projects, they find that aid is largely not allocated to the poorest regions. Despite Jablonski (2014) highlighting how governments often delegate aid management to recipient governments, Piva and Dodd (2009) help explain inefficient[1]

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[1] For simplification, I define 'efficient allocation' as aid going to those most in need. However, as will be discussed later, there are valid reasons why aid may be allocated according to other considerations but may still be considered "effective." This definition, though, provides a helpful benchmark for evaluating how

allocation by arguing that recipient governments may be limited in their ability to allocate effectively. They argue:

> "While global levels of health aid are clearly rising, it is less clear whether the amount of money available to countries to allocate flexibly, in accordance with their health priorities and health system development needs, is also increasing."

Additionally, Powell and Findley (2012) use sub-national analysis to examine donor coordination, where they define good coordination as donors clustering in areas with great need or spreading out in areas of diffuse need. Overall, they find lack of donor coordination and ineffective aid allocation.

Aid allocation is also influenced by political factors at the sub-national level. Jablonski (2014) geocodes multilateral aid projects in Kenya from 1992 to 2010 to show that "Kenyan governments have consistently influenced the aid allocation process in favor of co-partisan and co-ethnic votes."[2] Hodler and Raschky (2010) generalize this claim. They examine 22,850 regions in 91 aid recipient countries and find that in countries with poor political institutions, aid fuels favoritism and largely goes to the leader's birth region. Hodler and Raschky (2010) further show that donors may be limited in their ability to prevent governments in recipient countries from directing aid according to political considerations. However, some evidence suggests that health sector aid may be sparred being driven by political patronage. Dietrich (2011) argues that corrupt governments have incentives to comply with donor objectives in the health sector in

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[2] Jablonski (2014) further argues that, "[w]hile governments may care about economic development, disaster relief, or other development objectives, their first priority is to remain in power. As a result, governments will try to take advantage of the situation and use information donors are not privy to in order to ensure that electorally strategic voters receive higher levels of foreign aid. Donors often lack the ability—or willingness—to distinguish between the neediest and the most politically expedient recipients, and as a result, the latter may receive a larger share of aid. Moreover, by giving governments discretion over aid allocation, donors may inadvertently create a demand among voters that their elected representatives provide more aid to their districts."

order to justify additional flows in other sectors that may fuel rent seeking behavior. Therefore, examining how health aid allocation specifically responds to political factors could be particularly revealing.

2.2 The Impact of Foreign Health Aid

There is a lack of evidence to indicate that health aid should be pursued as a policy objective to promote increases in human welfare… Just like general aid, which is shown to have an insignificant effect on economic development, aid used specifically for health goals has an insignificant effect on human development.

—Claudia Williamson, 2008

The critics of foreign aid are wrong. A growing flood of data shows that death rates in many poor countries are falling sharply, and that aid-supported programs for health-care delivery have played a key role. Aid works; it saves lives.

—Jeffrey Sachs, 2012

The literature remains divided about the impact of foreign health aid. Some scholars fail to find significant relations between health aid and health outcomes, others find that aid does improve health outcomes, albeit to a small degree, while others praise the impacts of health aid, emphasizing the link between reducing disease burdens and promoting economic growth. Contrasting results represents a broader 'micro-macro' paradox, where macro-level analyses largely showed aid to be ineffective or minimally effective, while micro-level analysis praise the impacts of specific health projects (McGillivary et al 2005). Mosley (1986), who first drew attention to this paradox, questioned:

> What is going on? Is it true as the data suggest that aid projects are succeeding while aid as a whole is failing, if so how? Or do the data in fact deceive?

Howes, Otor, and Rogers (2011) summarize four reasons why the paradox might be true, or the "aggregate impact of aid [may be] less the sum of its parts:" (1) aid may be fungible, that is aid projects may succeed but the benefits may have occurred even if there was no aid funding;[3] (2) aid could put upward pressure on exchange rates if aid is used to purchase non-traded goods, having negative growth impacts, (3) aid may reduce citizen expectations of their government, leading to poor governance (also see Moss, Pettersson, and van de Walle 2006), and (4) aid may lead to a brain-drain of civil service members to the better-paying donor community, harming economic management and performance. In lieu of cross-national regressions, Picciotto (2009) uses case studies of World Bank project performance ratings to determine whether a micro-macro paradox exists or if discrepancies resulted from "data deception." He ultimately concludes that a paradox exists in a third of the cases, where negative effects of aggregate aid reduced macro-level impacts. However, Howes, Otor, and Rogers (2011) reevaluate Picciotto's study, finding that two-thirds of the cases that Picciotto argued had a micro-macro paradox had "nothing to do with negative effects of aggregate aid." Ultimately, they argue that while cross-national studies can be useful, "in the Picciotto case, the data do deceive."

Williamson (2008) first examined the impact of foreign aid specifically directed to the health sector. She examines the impact of health aid on a number of different health indicators and finds that while the estimators on health aid exhibit correct signs (aid having a positive impact), health aid does not show statistically significant impacts. As a result, she concludes that foreign health aid is ineffective and should not be pursued

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[3] For example, Swaropp and Devarajan (1998) present research that shows that "aid intended for crucial social and economic sectors often merely substitutes for spending that recipient governments would have undertaken anyway and the funds that are thereby freed up are spend for other purposes."

as a policy option. A number of scholars corroborate Williamson's (2008) results. Gebhard et al (2008) examine the impact of bilateral and multilateral health aid on a number of health indicators from 1980 to 2005. They find that health aid has a positive but negligible impact on health conditions, especially compared to the impact of GDP on health conditions. Ultimately, they conclude that, "health aid may not improve the health performance of the average recipient country." Similarly, Wilson (2011) finds that economic growth strongly impacts health conditions while health aid does not. Moreover, he argues that instead of causing improvements in health outcomes, foreign health aid instead goes to places that "have experienced the greatest mortality reductions in the recent past." In short, he argues that foreign health aid appears to follow success rather than cause it. Kizhakethalackal (2009) empirically examines the impact of health aid on infant mortality rates and incidence of tuberculosis using a number of econometric approaches. She robustly fails to find significant relations between health aid and health outcomes, and ultimately concludes that "health-aid does not work."

William Easterly (2003) is one of the largest critics of foreign aid. He argues that, at best, aid is equipped to "benefit some of the people some of the time," rather than "[try] to be the catalyst for society-wide transformation." Some empirical evidence corroborates this argument, finding that foreign health aid does have small impacts on health conditions, or "helps some of the people some of the time." Mishra and Newhouse (2007) examine the impact of health aid on infant mortality, using data on 118 countries. They find that health aid does have statistically significant impacts. Specifically, they find that "increasing per capita health aid by $1.60 per year is associated with 1.5 fewer deaths per thousand births." However, they conclude that this estimated effect is small, especially compared to targets set by the Millennium Development Goals. Taylor et al. (2013) analyze the literature that examines progress towards Millennium Development Goal five, which concerns improving maternal and reproductive health. They find that the literature points to aid being associated with small yet improving health outcomes. Furthermore, Feeny and Ouattara (2013) find that health aid has a statistically significant impact on increasing immunization against measles and Diphtheria-Pertussis-Tetanus (DPT) at the cross-national level, ultimately arguing that health aid does improve child health.

In opposition to Easterly, other scholars argue that foreign aid, especially health aid, can "be a catalyst for society wide transformation." Gallup and Sachs (2001) show that a 10% reduction in malaria is associated with 0.3% higher growth per year. They further report that malaria alone costs Africa over $12 billion annually, and in some African countries has slowed economic growth by as much as 1.3% per year. In a foreign affairs article, Shah (2013) purports that "[t]he story of malaria is inseparable from the history of poverty . . . Getting rid of this one disease could simultaneously slash mortality rates and inhibit a major drain on economic growth." In particular, disease burdens diminish the tax base a state can draw from due to a less productive workforce, hurt business by reducing workforce efficiency, disincentivize investment and tourism, and lower school achievement through stunting cognitive development ("Malaria control: the power of integrated action" 2014; Mouzin et al 2011; Suarez and Bradford 1993; Lorntz et al 2006; Monaghan et al 2008; Price-Smith 2008; Asenso-Okyere 2011). By reducing disease burdens, states theoretically can overcome these hurdles to development.

While macro-level studies remain inconclusive about health aid impacts, studies examining specific aid projects have found notable impacts of health aid. Demombynes and Trommlerova (2012) examine declines in infant mortality rates using demographic and health survey data in Kenya. They find that substantial declines in infant mortality are largely explained by uptakes of anti-malaria bed nets, which have been funded by foreign donors including the Gates Foundation, the Global Fund to Fight AIDS, Tuberculosis, and Malaria, among others. Additionally, in a longitudinal study of 3500 Kenyan children, Fegan et al (2007) found that using insecticide-treated bed nets reduced mortality risk by forty-four percent.

While the most optimistic accounts of aid projects come from the project-level, it is misleading to suggest that all aid projects are successful. For example, the Roll Back Malaria (RBM) Partnership was launched in 1998 as a way to provide a coordinated response against malaria ("RBM Mandate" 2014). However, some years after its launch it was largely considered a failure, with some arguing that it caused more harm than good. In 2005, The Lancet reported that since RBM's launch malaria rates increased, and the "loose association" of organizations of RBM that intended to avoid a strict management hierarchy "actually inhibited decision-making and limited accountability" ("Reversing the failures of Roll Back Malaria" 2005). The Lancet further noted that "technical advice, which should have been WHO's forte, was 'inadequate and sometimes conflicting," and that the "administrative turmoil cost lives." Despite this failure, the Lancet concluded that, "the right strategies applied in the right ways can have a profound impact on incidence and mortality for malaria."

While scholars have examined the impact of specific health focused aid projects, to date no-peer reviewed study has examined the aggregate impact of health aid within a country. Such an analysis provides a middle-ground for macro and project level analyses— the broader impacts of health aid within a country can be examined without aggregating health and aid measures to a single number as cross-national studies do. Finding beneficial impacts from aggregating aid at the sub-national level would give evidence to aid not being “less the sum of its parts,” giving less weight to potential negative impacts of aid. On the other hand, failing to find beneficial impacts could mean two things. First, it may represent a broader failure of health aid at the project level. Second, failing to find impacts at the sub-national level would highlight the pathways through which aid may have an impact at the project level but, due to negative consequences of aid, aggregate impacts may be unnoticeable. For example, Lu et al (2010) find that health aid reduces government health spending when examining aid impacts on health systems across sub-Saharan Africa, ultimately arguing that health aid weakens health systems (also see Farag et al 2009). This suggests that areas that receive aid may benefit from foreign donors, but in turn may benefit less from the government. If this is true, aid impacts may not be seen.

3. HEALTH AND HEALTH AID IN MALAWI

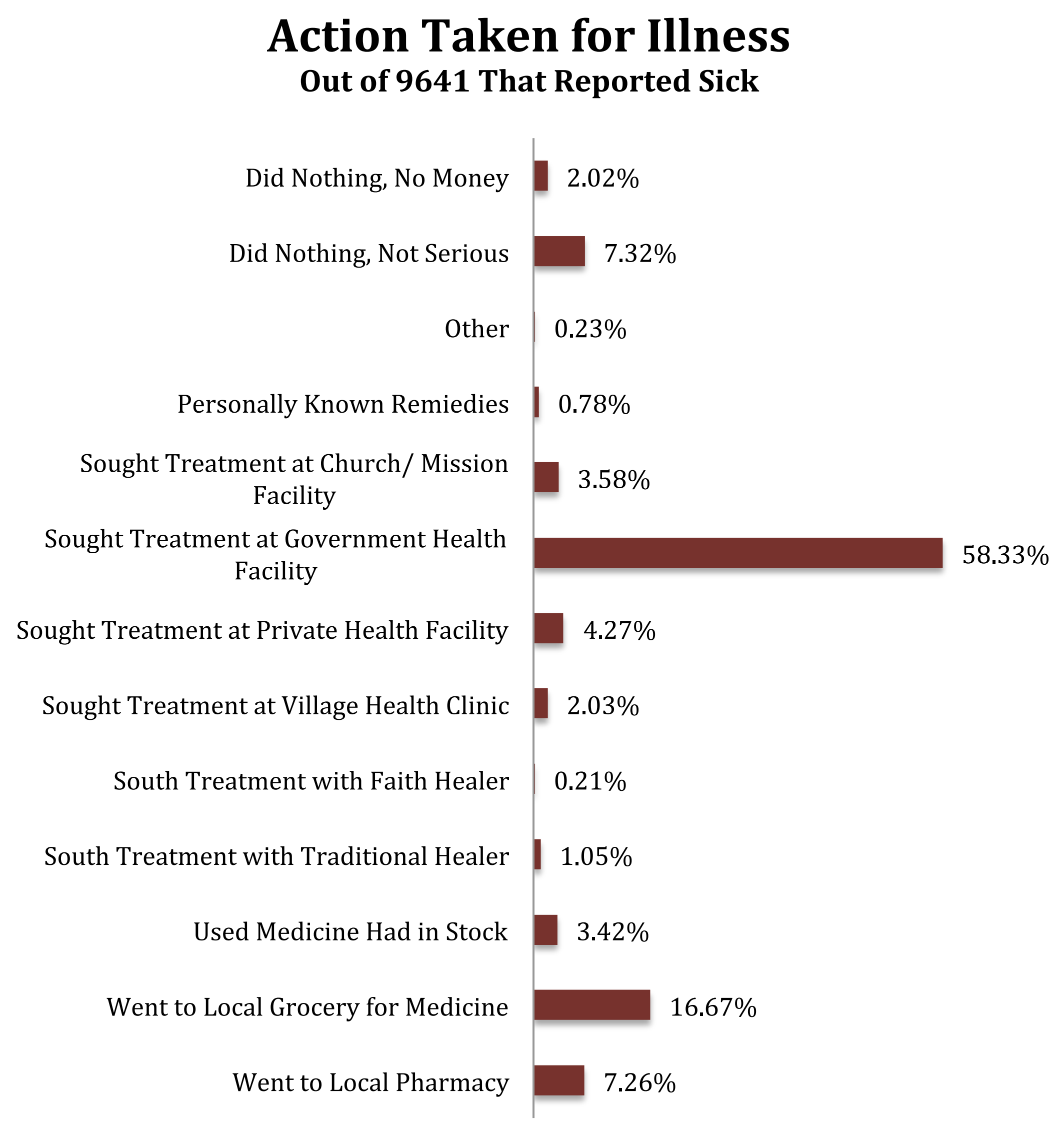
3.1 Burden of Disease and Health Infrastructure

Malawi remains one of the poorest countries in the world and faces substantial health problems. In a nation-wide survey conducted primarily in 2010, the World Bank asked respondents to rate on a scale of one to six whether they were among the poorest (one) or richest (six) in the country ("Malawi 2010 - 2011 - Third Integrated Household Survey" 2014). 71% of respondents answered one or two. Additionally, respondents were asked to rate their health care as less than adequate, adequate, or more than adequate. Out of the 56,218 individuals surveyed, 32% rated their health care inadequate, 61% rated their health care adequate, and only 7% rated their health care as more than adequate.

Malaria is one of the most prevalence diseases in Malawi. Out of a population of over 15 million, there are an estimated 8 million cases of malaria annually ("President's Malaria Initiative Malawi: Malaria Operational Plan FY 2013" 2013). However, while the WHO reports that cases of malaria generally increased since the early 2000s, there have been notable declines in recent years ("World Malaria Report" 2013). Specifically, the WHO reports that malaria incidence has declined from 356 cases per 1,000 people in 2006 to 325 cases in 2011 ("Malawi: Country Cooperation Strategy" 2013). Additionally, while Malawi faces among the highest rates of HIV in the world, HIV prevalence has consistently decreased since the 2000s. UNAIDs reports that HIV prevalence among 15 to 49 year olds decreased from 15.8% in 2000 to 10.8% in 2012 (“World Overview” 2014). Furthermore, the World Bank reports consistent declines in infant mortality rates. Since 2000, infant mortality rates have decreased by nearly 60%, from 173.9 deaths per 1,000 individuals to 71.0 deaths in 2012 (World Bank 2014).

The Malawi government has provided health care free of charge for most of its history as an independent nation (Messac 2013). World Bank survey results show a strong reliance on public health facilities. Out of a total 9641 people that reported sick in a 2010 survey, 58% went to a government health facility, while only about 4% went to a private health clinic (see Figure 1). However, growing financial constraints have

Figure 1. Action Taken for Illness



Data from the World Bank's Integrated Survey on Agriculture

prompted some government officials to suggest that compulsory fees may be introduced at hospitals (Messac 2013).

Public health institutions face a number of challenges, including drug and health supply shortages and a severe medical brain drain. Malawi's brain drain problem is one of the most severe throughout Africa. Low salaries, poor working conditions, and shortages of drugs and medical supplies have caused numbers of health professionals to find better opportunities abroad (Record and Mohiddin 2006). Its healthcare system faces an estimated shortfall of 160,000 health workers, and fewer than 4000 doctors, nurses, and midwives serve the entire population (Mangham 2007; Hall 2010). There is a total vacancy rate of 33% for medical professionals, with a 64% vacancy rate for nurses. To make up for health worker shortages, Malawi has used less qualified health workers, called "health surveillance assistants," to carry out tasks usually handled by physicians. To combat the brain drain problem, Malawi launched an Emergency Human Resources Plan in 2004 ("Malawi's Emergency Human Resources Programme" 2008). As a result of the program, medical training capacity has expanded, however health professional shortages still remain significant.

Inefficient health systems may partly result from poor governance. In 2013, the Pulitzer Center on Crisis Reporting reported that political leaders use healthcare to demonstrate benevolence, even when health facilities are under-par (Messac 2013). The Pulitzer Center reports one citizen saying that:

> "The politicians say that everything is in place. But the people go and find that not everything is in place. The quality of care is not what they were told. So the health sector is where the politicians play a lot of their games."

In 2013, Health Minister Catherine Gotani Hare admitted that Malawi's central drug warehouse only had 5% of medicines that the ministry deemed essential (Messac 2013). Theft by pharmacists and officials is cited as a major reason for medicine stock-outs. Clinicians have noted that long hours and low pay have led them to steal medicines as a means to make more money (Messac 2013).

Data from the 2010 World Bank survey highlights how poor health conditions are related to poverty levels (see Table 1), highlighting, as Shah (2013) argues, how disease and poverty are linked. On average, the wealthiest were able to spend over four times as much as the poorest. Additionally, 20% of the poorest individuals reported being sick, while only 7% of the wealthiest reported being sick. Interestingly, the average number of days individuals stopped normal activities due to illness appeared higher for the wealthiest. One explanation for this is that the poor are less able to afford taking days off, and are more likely to "tough it out" and work.

Table 1. Poverty and Health Conditions.

Poverty Level	**Amount Spent on Illness**	**Disease Prevalence**	**Average Days Lost if Sick**	**Health Care Quality**
1 (Most Poor)	18.21 (180.93)	0.203 (0.402)	3.28 (3.74)	1.68 (0.58)
2	15.20 (210.15)	0.170 (0.376)	2.93 (3.45)	1.75 (0.58)
3	21.25 (348.64)	0.151 (0.358)	2.52 (3.26)	1.81 (0.57)
4	58.08 (1147.49)	0.131 (0.337)	2.71 (3.38)	1.93 (0.52)
5	40.06 (541.38)	0.135 (0.342)	3.27 (4.00)	2.07 (0.45)
6 (Most Wealthy)	83.46 (611.76)	0.071 (0.258)	4.33 (4.69)	2.10 (0.53)

Average reported with standard deviation in parentheses. Data from the World Bank's Integrated Survey on Agriculture

3.2 Foreign Health Aid in Malawi

If donors say this is not democracy, to hell with you… yes, I'm using that word, tell them to go to hell.

—Former President Bingu wa Mutharika 2012

The donors have not walked away for the first time. They come and go and come and go but we are here, we did not die. Sometimes when these things happen, you grow up, you find other ways. We must become creative, we are not going to be dependent forever. Perhaps this is a golden opportunity for us. If we do certain things right and if we are as determined as we are as I sit here, in 10 years' time the donors shall be our partners, not our providers, and we shall have weaned ourselves from budget support.

—President Joyce Banda, 2013

Malawi has been dependent on foreign aid since it gained independence roughly fifty years ago (Tew 2008). Government revenues in 2006/07 were $990 million, $407 million of which came from foreign donors, which amounts to over forty percent of government spending coming from donors. Malawi's Aid Management Platform (AMP) reports Malawi receiving over $147 million in health aid since 2004, with health aid coming in a variety of forms and donors emphasizing different purposes. For example, in 2006 the World Bank gave $33.8 million towards an education sector project, which included health-sector focused goals of nutrition and food hygiene education, malaria control efforts, and helminthiasis control (Tierney et al 2011). The Norwegian Agency for International Cooperation (NORAD) consistently gives towards the health sector. In 2008 NORAD gave $9.7 million towards medical education and training, in 2009 gave $1.8 million towards providing medical equipment and supplies and providing support to clinics and hospitals, and in 2010 they gave $3.6 million towards developing basic health care infrastructure. Distribution of aid by year, purpose, and donors is reported in Figures 2 to 4 below and Tables 9 to 12 in Appendix.

Figure 2. Total Health Aid by Year.

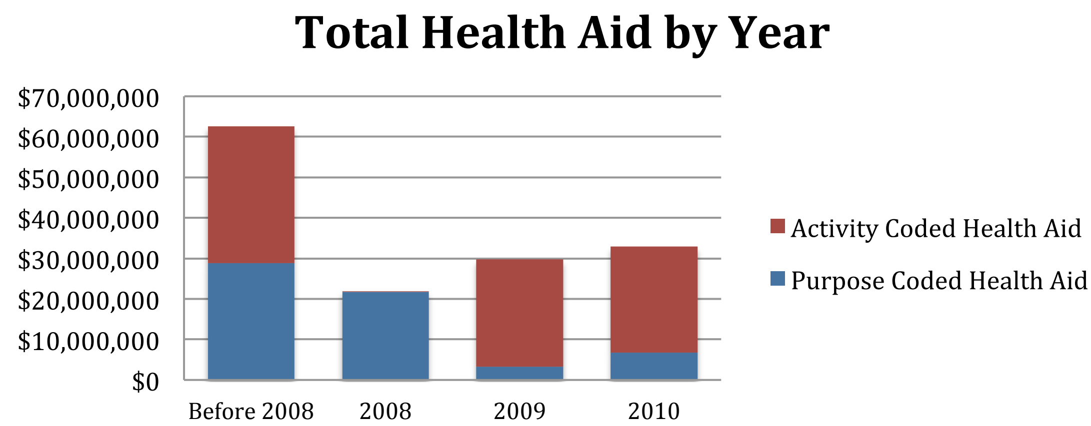
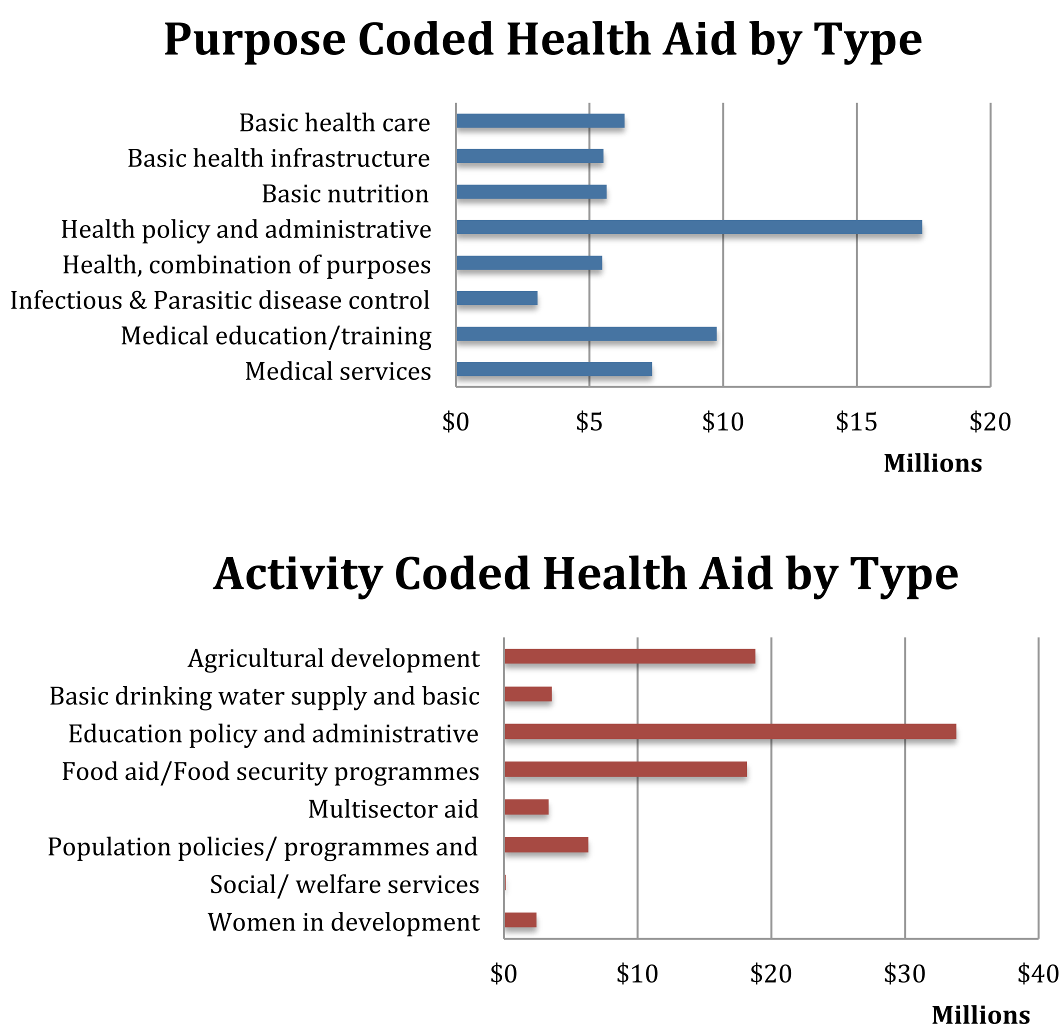
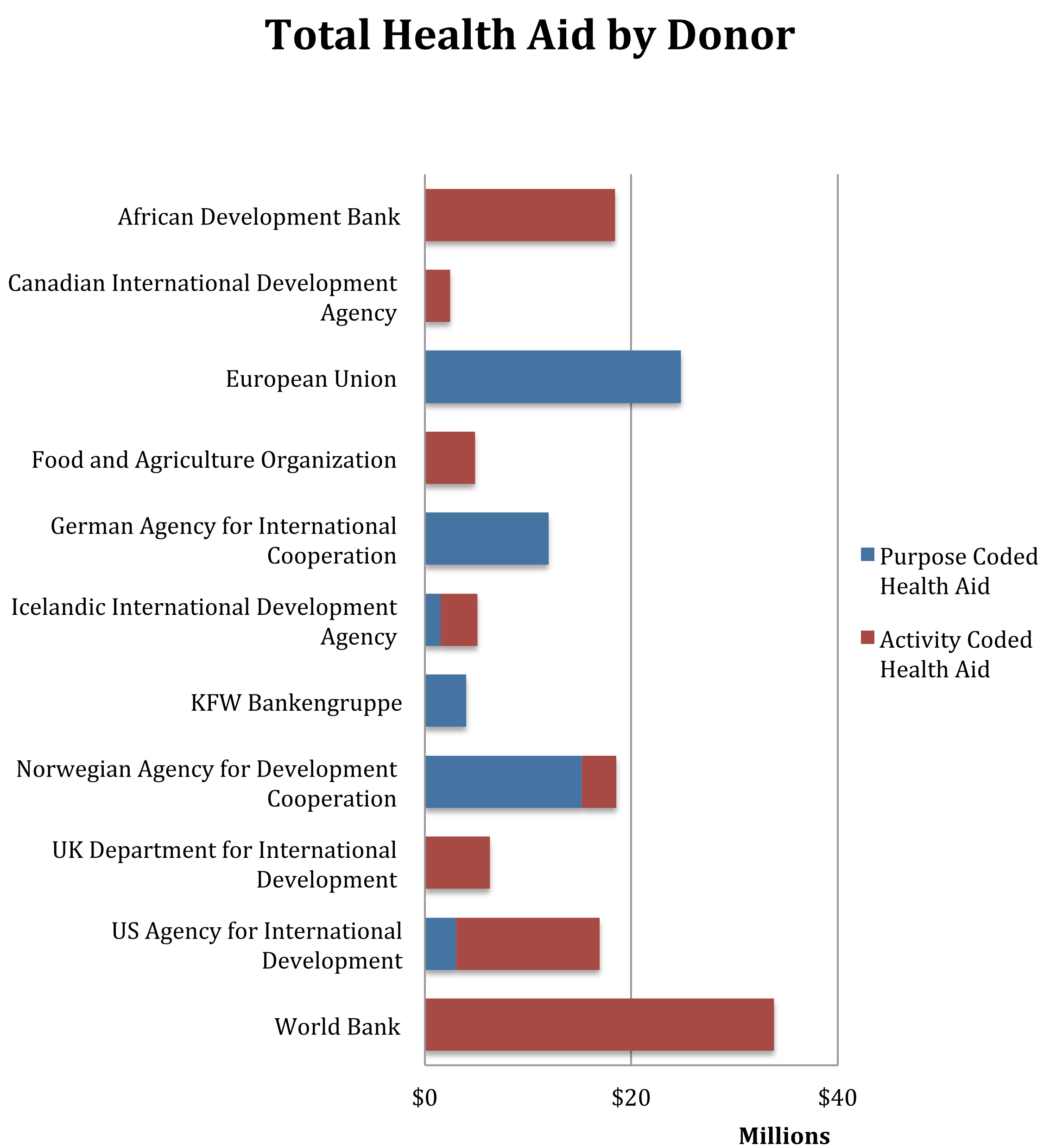


Figure 3. Type of Health Aid, by Purpose and Activity Coded Health Aid.



Data from AidData

Figure 4. Total Health Aid by Donor



Malawi's history has been fraught with cases of corruption and poor governance, which has caused backlash among donors and raised concerns about the misuse and mismanagement of foreign aid. Malawi's last president, Bingu wa Mutharika, served two terms from 2004 to 2012. His first term was characterized by good policies, which led to sound economic growth and encouraged donor support (Wroe 2012). However, his second term was plagued by corruption as he tried to consolidate power. In 2009 Mutharika used $12.9 million of public funds to buy a personal jet, which in turn caused the United Kingdom's Department for International Development (DfID) to withhold $4.8 million in foreign aid. In 2011 the European Union and DfID threatened to permanently end budgetary support if the government failed to address its concerns about unconstitutional behavior (Wroe 2012). The British High Commissioner, Fergus Cochrane-Dyet, highlighted worsening governance conditions, when a leaked cable reported him saying that Mutharika was "becoming ever more autocratic and intolerant of criticism" ("Malawi expels British," 2011). This caused the Malawi government to expel Cochrane-Dyet, which in turn caused Britain to choose not to renew a six-year funding commitment (Malawi: UK aid," 2011). Later in 2012 Mutharika told donors to "go to hell" after he heard (later disputed) reports that donors were working with NGOs to hold demonstrations against his rule ("Malawi's President Mutharika," 2012).

Poor governance and corruption during Mutharika's second term enraged civil society organizations, where one of their specific concerns was the impasse with foreign donors that Mutharika was creating. On July 20, 2011, protestors took to the streets, only to be met by armed government police, and eventually the army itself. This skirmish ended with the death of 19 people and upwards of 500 arrests (Mpaka 2011). Donors reacted harshly. Malawi's three largest donors, DfID, the EU, and USAID threatened to suspend aid indefinitely. The United States directly cited the violence as reason to withhold a $343.65 million aid package ("Us suspends aid," 2011).

The latest corruption scandal occurred in what was dubbed as the "cashgate" scandal. Here, upwards of eighty-one people were arrested for siphoning off up to $100 million in public funds for personal use (Dionne 2014). This raised serious questions of whether aid funds were used effectively, causing Britain, Norway, the EU, and others to withhold $150 million in aid from the Malawian government. Corruption scandals during Mutharika's second term caused funding to increasingly be given to NGOs rather than the government itself (Farrell 2012). In addition, poor governance and corruption have exacerbated poor health conditions. The cashgate scandal and its resulting financial consequences caused delays in payments to public health workers, sparking strikes throughout the country at public health facilities ("Government corruption "cripples" Malawi's health sector" 2013).

Mutharika's successor, current President Joyce Banda, came into office in 2012 and has made a concerted effort to shore up corruption and distance herself from Mutharika's policies. This has led to increased trust among donors, leading to a number of donors increasing funds. The African Development Bank alone pledged $45 million in aid to help Banda revive the weak economy (Baldauf 2012).

In light of poor governance and corruption donors have expressed a lack of confidence about the effectiveness of health aid specifically. For example, the Center for Strategic & International Studies (CSIS) reports that in 2010, "the Global Fund to fight AIDS, TB and Malaria rejected Malawi's application, which amounted to some $565 million, due in part to concerns about Malawi's capacity to implement the programs and its management of commodities" (Fleischman 2011). In addition, Norway's audit report of health aid to Malawi expresses concerns over the ineffective use of health aid ("Office of the Auditor General's investigation of Norwegian development aid to the health sector in Malawi" 2013). Their main findings indicate that while “development in Malawi has had a positive impact on maternal and child health and access to basic health care services, [the] key goal of reducing mortality and strengthening the health system has not been attained.” In particular, they note “a high degree of inefficiency in resource flows to hospitals and health centres in Malawi, which, among other things, translates into loss of medicines and lower availability of health personnel.” They note that this results in the “population receiving considerably fewer benefits for the funds allocated to health purposes than what could have been the case.” In addition, they highlight a lack of transparency, where in some cases no explanation is given for how funds are used.

While donors like Norway highlight inefficiencies and minimal aid impacts, other donors tell a different story. The UK’s DfID notes deteriorating health conditions up until the mid 2000s, when donors began investing more heavily into improving health conditions. DfID’s audit report of aid to Malawi attributes improvements in health services and health conditions to donor investments ("Department for International Development: Aid to Malawi" 2009). In particular, to combat Malawi’s brain drain, DfID helped to subsidize the wages of medical professionals, which has helped to cut the numbers leaving by over 50 percent (Hall 2010). This was part of Malawi’s Emergency Human Resources Programme (EHRP), which the Malawi government reports has saved nearly 13,000 lives ("Malawi's Emergency Human Resources Programme" 2008; Mweninguwe 2012). In addition, praise for health aid goes beyond DfID. The director of the Malawi Health Equity Network, Martha Kwataine, praised investments from USAID in enabling her organization to help reopen maternity wards, staff clinics, and ultimately provide upwards of 10,000 people access to basic health services (Kwataine 2013).

Additionally, the beneficial impacts of health aid can be seen from the affects of reductions in aid funds. Funding cuts heightened drug shortages and stock-outs, as well as exacerbated other health challenges (Malawi: UK aid," 2011). Chief Kwataine, who oversees the district Ntcheu in central Malawi, said that "[The cuts] will really make a difference because we don't have the means to buy most drugs ourselves" (Martin 2013). Indeed, Malawi heavily relies on donor support for medicines and health supplies. Foreign aid covers about 90% of the costs of medicines in Malawi, and anti-retrovirals are provided entirely by foreign donors (Malawi: UK aid," 2011).

Different accounts of aid effectiveness highlight how the overall impact of health aid within Malawi is not clear. Norway's audit report of health aid emphasizes concerns about the ineffective use of foreign aid funds, and donors have halted funding due to corruption and poor governance. However, DfID's audit report emphasizes improving health conditions as a result of foreign aid, and both NGO leaders and government officials in Malawi praise the impact of foreign health aid. Furthermore, poor governance and corruption highlight the possibility that patronage has influenced aid allocation, which raises questions as to whether health aid has been directed to those most in need, and, more generally, how aid funds have been managed. To provide further insight of health aid in Malawi, and of the broader aid effectiveness debate, I empirically examine the allocation and overall impact of health aid in Malawi in the sections that follow.

4. DATA

Shedding light on the geographic dimension of aid can have a powerful and catalytic effect on the impact of development.

—AidData Co-Executive Director Nancy Choi, 2014

It is possible to examine aid at the sub-national level due to efforts of the AidData Center for Development Policy in geocoding aid projects. AidData, in partnership with Malawi's Ministry of Finance, produced the first fully geocoded dataset of aid projects for a specific country (Tierney et al 2011). Health and control variables primarily come from the Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) dataset ("Integrated Household Survey 2010-2011" 2012). This is a $19 million dollar survey project funded by the Bill & Melinda Gates Foundation, which conducts surveys across seven countries throughout multiple years. I utilize Malawi's Third Integrated Household Survey, which collected data from March 2010 to 2011. 12,271 households were included in the survey, representing 56,218 individuals (for full descriptions of all variables, see Table 15 in Appendix). According to a report by Malawi's National Statistical Office, the survey was designed, "to be representative at both national, district, urban and rural levels enabling the provision of reliable estimates for these levels" ("Integrated Household Survey 2010-2011" 2012).

Foreign Health Aid

Malawi's geocoded data come from its Aid Management Platform (AMP), which was implemented in 2008 as a way to better collect and organize aid flow information (Petras 2009). The dataset includes projects from 30 donor agencies, representing $5.3 billion in aid commitments (Tierney et al 2011). Additionally, the data represent about

80% of external aid reported to the Malawi Ministry of Finance since 2000. Aid disbursement data are collected on a monthly basis, and donors are asked to validate the data.

While geocoding much of the data from Malawi's AMP provides a significant step towards improved aid transparency, the data are not without its setbacks. Historical data prior to the implementation of the AMP are included; however, data prior to implementation are considered incomplete (Petras 2009). Additionally, Malawi's AMP data does not include donors that do not have an office in Malawi. This is because aid reports are obtained from in-country staff of donor agencies that have a presence in Malawi. Donors not present represent about 10% of total aid. Furthermore, AMP data excludes aid projects implemented by NGOs. NGOs are not directly accountable to the government, and therefore are not required to report data. However, NGO data are captured if a donor that reports to the AMP funds the NGO.

Knowledge of aid flows is also limited by donor transparency. A number of non-Western governments have increasingly given foreign aid, however do not report official aid flows. Such donors include Saudi Arabia, China, Iran, and Venezuela ("Tracking Chinese Development Finance to Africa" 2014). To start to track underreported aid flows, AidData has compiled a database of Chinese aid flows by examining media reports of aid projects. This database reports 23 aid projects from China to Malawi, given from 2005 to 2012. However, only one aid project was designated as health aid, with an undetermined financial value. Therefore, not including Chinese aid will likely not skew results. However, information on other non-Western donors is not available and therefore how these undisclosed aid sources skew analyses cannot be assessed.

AidData categorizes the type of aid by a purpose and activity code scheme ("AidData's User Guide: Version 2.0" 2011). Purpose codes designate the primary purpose of the aid project, while activity codes designate specific activities of aid projects. I create aid variables according to two definitions of health aid: one limited to aid projects with a health purpose code (purpose codes starting with "12"), and health aid variables that include projects with either health purpose or activity codes. Creating health aid variables that only include projects with a health-related purpose code keeps the focus on projects specifically designed to improve health outcomes. However, "purpose and activity coded" health aid variables include projects not directly intended to improve health but which may also have an impact.[4]

Additionally, I distinguish aid by year. I include aid in 2010, 2009, 2008, and before 2008. Dates are defined as years that aid projects where expected to be completed. I limit analyzing aid up to 2010 to match LSMS-ISA data, which was collected from March 2010 to March 2011. Additionally, I lump before 2008 data together because AMP data before 2008 are incomplete and are more scarce.

I also consider the precision code of aid projects. Precision codes reference whether aid was given to specific locations (specified by an exact latitude and longitude) or to larger administrative areas. Foreign health aid projects included three precision codes, aid to an exact location (a "1" precision code), aid to an exact location but with

[4] Activity codes often refer to activities that are different from the specific purpose. For example, an aid project with the purpose of improving sanitation would be designated with a "water supply and sanitation" purpose code. However, such a project may include a health activity code if the project references improving health outcomes. For example, the United Kingdom DfID highlights how projects in other sectors, especially water and sanitation projects, have direct health impacts ("Department for International Development: Aid to Malawi" 2009).

uncertainty of exactly where (a “2” precision code), and aid given to a district (a “3” precision code).[5]

For aid given to an exact location, theory does not indicate how far the aid project has an impact. Because I cannot conclusively determine the distance, on average, that aid has an impact I examine aid at three different “aid impact zones”. I create buffers around aid given to an exact location (aid with precision codes 1 and 2) using three different radii: 5 miles, 10 miles, and 15 miles. Aid projects with a “2” precision code are considered as if they are coded as “1.” This doesn’t account for the uncertainty of where precision coded “2” projects actually went; however, out of 189 precision codes, only four were coded with “2.” Therefore, this should not skew the results.

Ultimately, I combine district-level and point-location aid projects together for each year. This creates final health aid variables that delineate areas in Malawi that received aid. The percentages of individuals from the LSMS-ISA dataset that were in areas that received aid are reported in Tables 2 and 3, according to different years, the two variations of health aid, and the three different aid impact zones for point-location aid.

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[5] Health projects in the Aid Malawi Aid Management Platform dataset include three
According to the AidData geocoding codebook, the three precision codes are defined as:
1 = The coordinates corresponds to an exact location, such as a populated place or a hill.
2 = The location is mentioned in the source as being “near”, in the “area” of, or up to 25 km away from an exact location. The coordinates refer to that adjacent, exact, location.
3 = The location is, or is analogous to, a second order administrative division (ADM2), such as a district, municipality or commune.

Table 2. *Percentage of people in training data that were in an area that received purpose code foreign health aid.*

	Before 2008	2008	2009	2010
5-mile radius	13.2%	37.6%	6.9%	60.1%
10-mile radius	19.2%	44.0%	8.8%	62.2%
15-mile radius	24.4%	51.6%	10.9%	64.7%

Table 3. *Percentage of people in training data that were in an area that received purpose and activity code foreign health aid.*

	Before 2008	2008	2009	2010
5-mile radius	14.3%	47.0%	78.6%	79.8%
10-mile radius	20.1%	53.0%	84.0%	81.8%
15-mile radius	26.4%	59.6%	90.0%	83.5%

Additionally, in all analyses I use foreign aid as a binary variable. There are drawbacks to examining aid as a binary in lieu of considering aid amounts. In particular, questions regarding why areas receive more aid than others cannot be examined. However, I use a binary variable to keep aid variables consistent across analyses. In section 5.3, which examines the causal impacts of aid, propensity scores developed to compare individuals who did and did not receive aid come from logistic regressions, which require that aid be a binary variable. Therefore, to confidently compare results across empirical analyses, I keep aid variables the same.

Disease Incidence

Disease incidence data comes from the LSMS-ISA, and measures whether a person suffered an illness or injury in the two weeks prior to being surveyed. Disease incidence serves as the dependent variable in aid impact models and a control variable in allocation models. Effective foreign aid would predict that aid reduces disease incidence, and that aid goes to places with higher disease burdens.

Another variable in the LSMS-ISA data that could have been used to measure health conditions is "disease severity," or the number of days a person had to stop normal activities because they were sick.[6] However, I use disease prevalence because foreign health aid generally seeks to reduce disease burdens or eliminate cases of disease, rather than reduce the disease burden on people once they are sick. For example, programs to distribute bed nets to combat malaria intend to *prevent* people from contracting malaria, versus alleviating the burden once they contract the disease ("Insecticide-Treated Bed Nets" 2014).

Health Care Quality and Accessibility

Health care quality data comes from the LSMS-ISA. Surveyors asked respondents to rate their health care quality on a scale from one to three (one for health care quality being less than adequate, and three for more than adequate). Health care quality is predicted to be associated with less disease, and effective aid allocation would suggest aid going to places with worse health care.

Additionally, I include a variable that measures distance from a health facility. Due to low financial resources, people often struggle to afford transportations costs to get to health centers (Messac 2013; Kwataine 2013). Fuel scarcities have compounded the difficulties in traveling long distances to health clinics (Kwataine 2013). Therefore, less accessibility may be associated with increased disease burdens and a greater need for health aid. Clinic location data comes from the Malawi Ministry of Health, and I measure

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[6] A similar paper by De (2013) uses 'disease severity' as an indicator for health conditions. See: De Rajlakshmi, "Foreign Aid Allocation and Impact: A Sub-National Analysis of Malawi," *Duke University* (2013), https://econ.duke.edu/uploads/media_items/raj-de-dje-aid.original.pdf.

the Euclidian distance (in kilometers) from health facilities ("Health Facilities - Ministry of Health" 2013).

Population

Studies of aid allocation and impact typically include a population variable. Less populated areas tend to have greater need; however providing aid to less populated areas may be more costly (Pietschmann 2014). This is true of Malawi, where 14% are considered poor[7] in urban areas, while 43% are considered poor in rural areas (Mussa and Pauw 2011). Therefore, population levels could influence both aid allocation and risk of disease. I test two population variables: distance to a population center and population density. Distance to a population center comes from the LSMS-ISA dataset, and measures the distance in kilometers to a population center of over 20,000 people. Population density comes from the Center for International Earth Science Information Network, and is the population per square kilometer (Center for International Earth Science Information Network 2011). To simplify interpretation, I convert the unit of analysis to 100 people per sq. kilometer.[8] Because theory does not suggest which population variable is better to include, I test both variables.

Poverty Levels

Poverty levels could affect both aid allocation and health outcomes. Individuals with fewer resources may be at greater risk of being sick. Therefore, health aid may go to individuals with fewer resources. Two variables from the LSMS-ISA dataset measure

[7] Mussa and Pauw (2011) define ‘poor’ as being under the poverty line of making US$575 per year.
[8] This is done because increasing population density by one person likely will have very small estimators.

poverty. The first is a 'poverty level' variable, which asks respondents to rate their income on a scale of one to five — one being income allowing the individual to build their savings, and five being insufficient income and the person needing to borrow to meet expenses. The second is a 'wealth perception' variable, where individuals are asked to rate on a scale from one to six whether they are among the poorest or richest in the country (one being poor and six being rich). Both variables measure poverty or financial status; however, theory does indicate which variable would better fit the data. Therefore, I test both variables.

Presidential Ethnic Match

To account for potential ethnic patronage, I create a 'Presidential Ethnic Match' variable, which indicates whether a person lives in an area that is dominantly of the Lomwe ethnic group, which is the ethnic group of former president Bingu wa Mutharika (see Figure 13 in the appendix to see where Lomwe individuals are located in Malawi). Political patronage has previously shaped the provision of public goods in Malawi (Wild and Harris 2012; Cammack and Kanyongolo 2010). In particular, ethnic divisions have played a role in Malawi politics. Ethnic divisions became particularly apparent after Mutharika's reelection in 2009. After coming into office, Mutharika gave leaders in his ethnic group power throughout all branches and at different levels of government (Nyasa Times 2009). Data comes from Malawi's 2008 census, which reported ethnic group prevalence in the 12,567 Enumeration Areas across Malawi ("Population and Housing Census" 2008). Mutharika's presidency (from 2004 to 2012) spans the data used (the earliest reported aid flow occurs in 2004). Therefore, this variable is appropriate to test for all years.

Environmental Risk Factors

Environmental factors influence the risk of contracting an illness. This is especially so with malaria, which is the most prevalent disease reported in the LSMS-ISA dataset (see Table 8 in appendix). Malaria risk has been shown to be particularly associated with elevation, temperature, and rainfall (Kazembe et al 2006; Lowe, Chirombo, and Tompkins 2013). Following these results, I include elevation, temperature, and rainfall estimates, which are included in the LSMS-ISA data. Higher temperatures and precipitation and lower elevations are associated with higher incidences of Malaria (Kazembe et. al 2006; Odongo-Aginya, Ssegwanyi, and Vuzi 2005). In addition, I include the variables as quadratics to account for nonlinear relationships. For example, while higher temperatures are associated with more active malaria vectors, too high of temperatures could prove harmful to malaria vectors (Kazembe et. al 2006). Environmental factors influence disease incidence and could also influence aid allocation, as health aid may go to areas more at risk for malaria. The dataset reports temperature in units of 0.1 ^{0}C, and to simplify interpretation for other variables I convert elevation to units of 10 m and precipitation to 10 mm.[9]

[9] This was done by dividing original variables by 10.

5. EMPIRICAL ANALYSIS

I empirically estimate the determinants of aid allocation and disease prevalence, as well as estimate the causal impact of health aid on health outcomes. First, I use AIC model averaging to examine which factors drive aid allocation. Second, I use the same approach to examine which factors explain health outcomes. Here I ask how important foreign health aid is relative to other variables. Third, I bring analyses of aid allocation and aid impact together. I use propensity-matching methods to examine the causal impact of foreign health aid on disease incidence, using allocation models to develop propensity scores.

All analyses involve prediction, whether it is predicting health outcomes or aid allocation. Therefore, validating the models is especially important. For all analyses, I randomly select 90% of the data as training data, leaving the remaining 10% for external model validation. With a total of 56,218 data points, this leaves 50,596 in the training dataset and 5,622 in the testing dataset. I conduct both internal and external validation of models. For external validation, I examine how well models developed from the training dataset explain actual values in the testing dataset. I conduct simple regressions with actual and predicted values, examining the r-squared value. I conduct internal validation using the area under the receiver operating characteristic curve (ROC). ROC areas measure the ability of a model to classify people into distinct groups (Fawcett 2005). A ROC value of 0.5 indicates that the model was as good as random assignment (and thus is a worthless model), while a ROC value of 1 indicates that the model is perfectly predictive.

5.1 Aid Allocation: Why Does Aid Go Where it Goes?

Methods

I estimate the determinations of foreign health aid across all years. Here, I ask which variables are most important in explaining why foreign aid is given to a specific location, and how determinants of aid allocation change throughout time. While all years are considered, independent variables from the LSMS-ISA represent 2010 data. While some factors considered do not change over the years considered (such as elevation and ethnic match with president), others do change (such as such as poverty levels and health care quality). Therefore, using data collected in 2010 to explain aid allocation in the past is not ideal. However, such social variables likely change slowly overtime, and therefore give an approximate indication for conditions in the past.

For model selection, I compare models according to their Akaike information criterion (AIC) (Burnham and Anderson 1998). AIC measures the quality of a statistical model, where it balances goodness of fit and model complexity. The AIC value itself is an estimate of the information lost by a model "to approximate the process that generated the observed data" (Johnson and Omland 2004). AIC values do not express the absolute quality of a model, but are used to compare between other models. The model with the lowest AIC value is considered the best model to fit the data (Burnham and Anderson 1998; Bozdogan 2000). AIC is calculated as:

$$AIC = 2P - 2\ln\,[L(\hat{\theta}_P|y]$$

where P represents the number of parameters and $L(\hat{\theta}_P|y)$ represents the likelihood of the model parameters (using the maximum likelihood estimates of the parameters) given data y (Johnson and Omland 2004). As seen from the equation, AIC penalizes model complexity (including additional variables) and preferences goodness of fit of the model (Bozdogan 2000).

I conduct model averaging using AIC values to develop final models. Models with all possible combinations of variables are considered as candidate models. Then, the parameter estimates of the top models (according to their AIC weight) within a 95 percent confidence set are averaged together using weighted averages based on AIC weights . To develop the confidence set, each model is given an AIC weight according to the difference in the AIC of the model compared the model with the lowest AIC value (Burnham and Anderson 1998, Johnson and Omland 2004). The 'likelihood' of a model (or, more specifically, the likelihood that a model structure is the correct model structure in explaining an outcome) is calculated as:

$$likelihood = \exp\left(-\frac{1}{2} \times \Delta AIC\right)$$

where ΔAIC is the difference between the model AIC and the lowest AIC value. Model likelihood values are then normalized across all models so they sum to one.[10] This is done by dividing the individual model likelihood by the sum of all model likelihood models (Burnham and Anderson 1998). I create a 95 percent confidence set of models, where I calculate a weighted average of all models where the sum of their normalized likelihoods adds up to 95. From this, variables importance can be denoted by the sum of normalized likelihoods of the models they are in. For example, if a variable is included in all models in the 95 percent confidence set, it will have an AIC likelihood of one.[11]

[10] Normalized likelihood values also serve as weights for creating final models, as final models are created through taking a weighted average of all models in the 95 percent confidence set.

[11] Making a 95 percent confidence set means that if a variable is included in all models in the set, it technically will have a normalized likelihood of .95. However, I adjust weights in the 95 percent confidence set so they sum to one. Not adjusting likelihoods to equal one would lower estimator values.

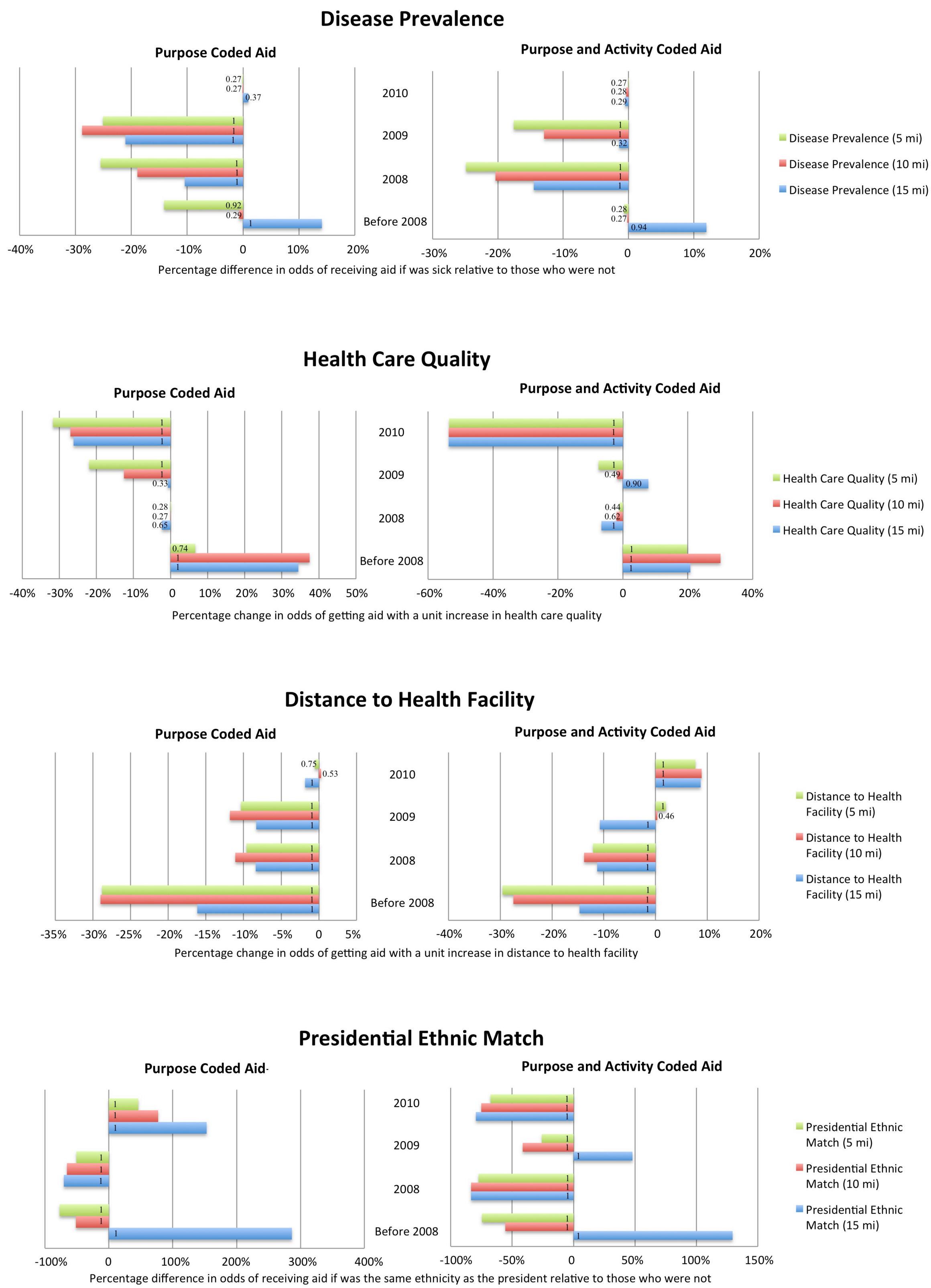
Model averaging was developed to address the uncertainty inherent in model selection (Burnham and Anderson 1998). While researchers virtually always address uncertainty of estimators through standard errors, uncertainty of estimator values through model structure often goes unaddressed (Bartels 1997; Burnham and Anderson 1998; Moral-Benito 2013; Hoeting et al. 1999; Jackson, Thompson, and Sharples 2008; Montgomery and Nyhan 2010). Figures 14 and 15 highlight how estimator values change as the model structure changes.

Model averaging is suggested when (1) theory is underdeveloped and provides little guidance for model selection and (2) when a number of models could be regarded as a potential hypothesis of the true model (Moral-Benito 2011; Moral-Benito 2013). Both of these conditions fit aid allocation and impact at the sub-national level, as such analysis have only recently started to be examined. The model averaging approach views each model structure as a hypothesis for explaining an outcome. Here, all possible combinations of independent variables could be viewed as hypothesis. For example, donors giving health aid may respond strongly to poor health care quality while poverty variables may not be as important. Therefore, this model structure would exclude poverty variables. Furthermore, environmental variables may prove insignificant as donors respond to social and health variables rather than where there is a higher environmental risk for disease. Additionally, governments may disregard socio-economic conditions and allocate aid strictly to political factors. Further hypotheses are theoretically justified by considering constraints governments may face in allocated according to socio-economic conditions (Piva and Dodd 2009). Therefore, allowing all possible models to compete is justified as all possible model structures are theoretically defensible.

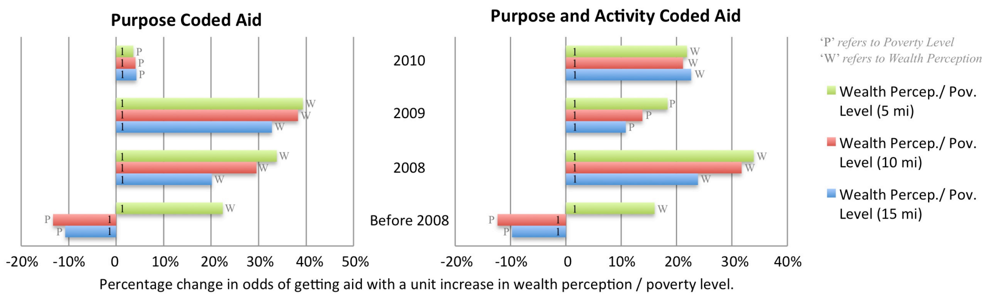
Six final models are developed for each year, which comes from examining the two different versions of foreign health aid at three different aid impact zones. Because the dependent variable is binary (an individual being in an area that received health aid or not), all models are developed from logistic regressions. I run all possible combinations of control variables on each dependent aid variable. However, I exclude some variables from being in the same model. First, I exclude variables that measure similar factors from being in the same model (such as the poverty level and wealth perception, and distance to a population center and population density). Second, I exclude variables that are highly correlated to avoid issues of multicollinearity. Temperature and elevation highly correlate ($r = 0.9$), and thus are excluded from being in the same model (see Table 14 in Appendix).

While the above variable combinations cannot be in the same model, I also exclude them from being weighted together. I keep the variables included in the best models. For instance, if poverty level (rather than wealth perception) appears in the best model, I eliminate all models with wealth perception in them. Results are presented in Figure 5 along with model diagnostics in Figure 6 (in addition, see Tables 16 to 21 in appendix).

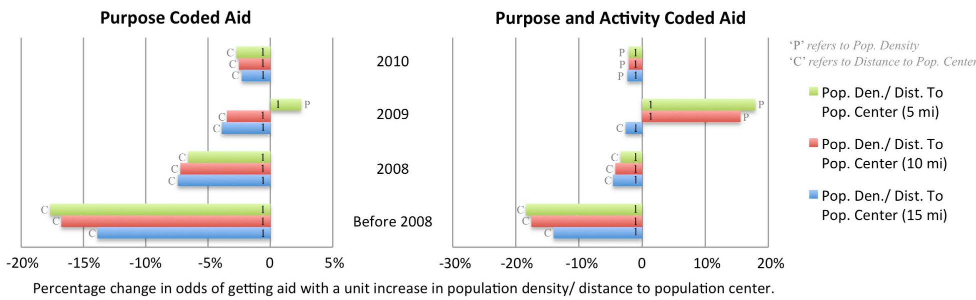
Figure 5. Aid Allocation. *Percentage change in odds of receiving aid reported for each variable. AIC weights reported in bar graphs.*



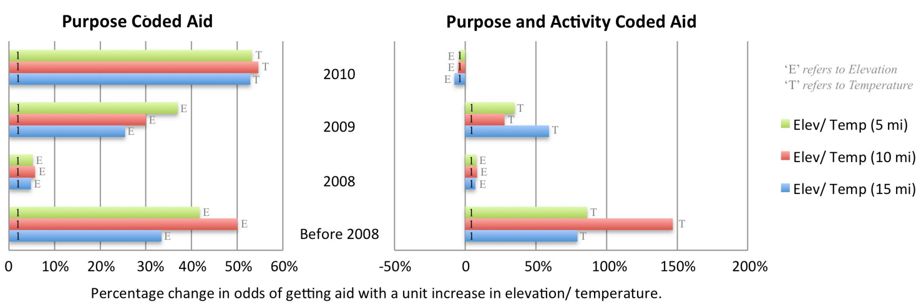
Wealth Perception/ Poverty Level



Population Density/ Distance to Population Center



Elevation/ Temperature



Precipitation

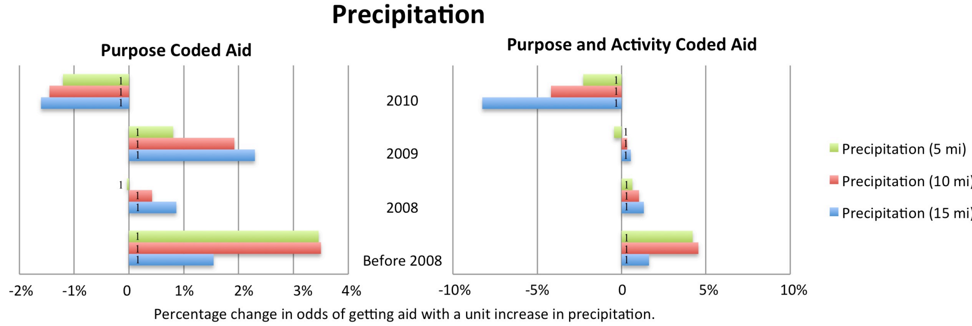
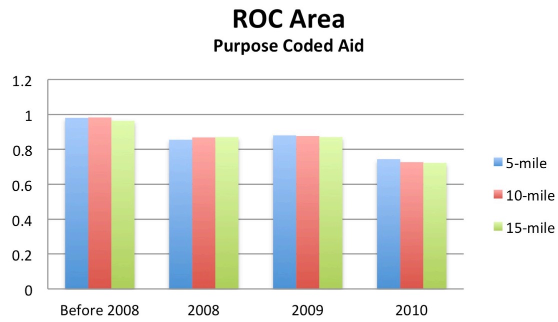


Figure 6. Internal Model Validation



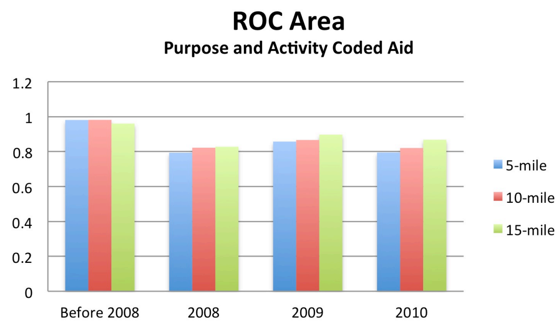
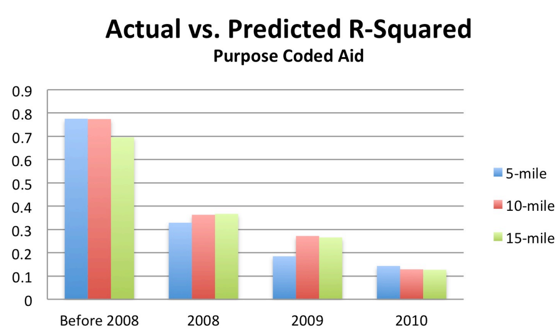
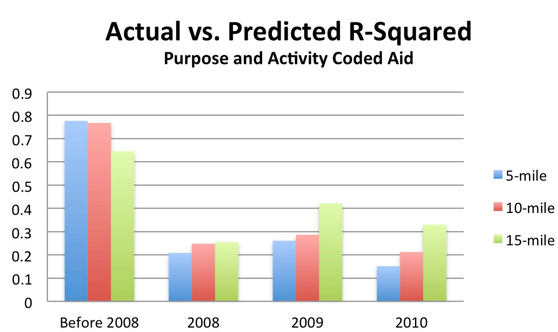


Figure 7. External Model Validation





Results

Internal and external validation overall shows models to be predictive. Models for before 2008 aid appear the most predictive, having ROC values > 0.9 and r-squared of regressions between actual versus predictive values > 0.7. 2010 aid had the lowest values, but still showed the model to be relatively predictive. Here, ROC values are between 0.7 and 0.8, and r-squared of regressions between actual versus predictive values between 0.1 and 0.3, which suggests decently strong models. Models may have been particularly strong for before 2008 because all aid was precision coded at a specific area, meaning there was no district level aid. Aid projects covering smaller geographic areas decreases the chance that people were in areas that received aid but did not benefit. Therefore, having no district level aid projects may have improved model validation measures. However, models with district-level aid still appear predictive (see Figures 6 and 7 for mode validation summaries).

Results are mixed as to whether aid was allocated to areas with the worst health conditions. Overall, aid was generally not allocated to places with higher disease burdens. In 2010 disease burdens was a relatively unimportant variable, but in 2008 and 2009 being sick was associated with about a 10 - 20% reduction in odds of receiving aid. However, effective aid allocation is generally seen when examining health care quality from 2008 to 2010, but to varying degrees. Worse health care quality was associated with receiving more aid, with the magnitude of the estimator and AIC weights growing over time. In 2010, a one unit decrease in health care quality (for example, from adequate to inadequate) is associated with about 30% increase in odds of receiving aid for purpose coded aid and about fifty percent greater odds of receiving purpose and activity coded aid. However, a one unit decrease in 2008 corresponds to $\leq 2\%$ increase in odds of receiving purpose coded aid and 6% increase in odds of receiving purpose and activity coded aid. In addition, in 2010 health care quality has AIC weights of one (for both variations of health aid), while AIC weights drop to as low as 0.26 in 2008.

Analyses show that aid was generally not allocated to the poorest individuals. For purpose coded aid, only in 2010 was increased poverty associated with receiving more aid, while for purpose and activity coded aid only in 2009 was increased poverty associated with receiving more aid. In other years, a one-unit increase in wealth perception or a one-unit decrease in poverty level was associated with 10 – 40% increase in odds of receiving aid, depending on year and aid impact zone.

Increases in distances to health facilities are generally associated with receiving less aid, which suggests that aid projects may not go to more rural or hard to reach areas. This result corroborates with how population acts as a determinant of aid. Results generally show that higher populations or being closer to a population center are associated with receiving more aid. The only year that breaks this trend is purpose and activity coded aid in 2010. Additionally, for purpose coded aid the estimator on Distance to Population Center decreases over time. Before 2008, a one-kilometer increase in distance to a population center is associated with about 15% reduction in odds of receiving aid. However, in 2010 a one-kilometer increase is associated with only about 2.5% reduction in odds of receiving aid. This suggests that, over time, purpose coded health aid increasingly was directed to relatively less populated areas.

Environmental health risk factors are consistently important variables with AIC weights of one. Most years show increased environmental risk associated with more health aid in terms of elevation/ temperature, precipitation, or both. Additionally, like with many variables, allocation differs over time. Purpose coded aid shows that before 2010, higher elevations were associated with receiving more aid, meaning that areas less at risk for malaria received more aid. However, in 2010 areas with higher temperatures (and at a greater risk for malaria) were more likely to receive purpose coded aid. While purpose coded aid shows that only in 2010 was aid was allocated to individuals more at risk for malaria (in terms of elevation/ temperature), purpose and activity coded aid shows effective allocation in 2010, 2009, and before 2008. Additionally, increased precipitation (meaning greater risk for disease) was generally associated with receiving more aid for all years except 2010.

Differences in aid allocation across years could be explained by different aid projects being more needed in certain areas. For example, only in 2010 did purpose coded aid go to places with higher risk of malaria (in terms of temperature/ elevation). Here, nearly half of aid flows were a USAID project devoted towards "infectious and parasitic disease control" (see Table 10 in appendix). Therefore, it makes sense that aid in this year would be allocated to areas with greater malaria risk. Additionally, while 2009 purpose coded aid did not go to areas with greatest malaria risk, individuals with worse health care had 10 – 20% increase in odds of receiving aid (when considering the five and ten mile aid impact zones). This makes sense when examining the type of aid given, as nearly half of aid was devoted towards improving basic health infrastructure. However, comparing the types of aid projects with how aid was allocated also shows cases where aid may not have been allocated effectively. For example, nearly a third of 2008 purpose coded aid went towards improving basic health care; however, allocation results show health care quality as a relatively unimportant variable, having AIC weights , 0.3 at the five and 10-mi aid impact zone and an AIC weight of 65 at the 15-mi aid impact zone. Overall, while results are mixed as to whether aid goes to those with greatest need, results do highlight how defining ‘need,’ whether that be low socio-economic status, poor health care, or significant risk of disease influences conclusions about effective aid allocation.

Results show evidence that political factors may have influenced health aid allocation in 2010. Purpose-coded aid in 2010 shows individuals in the same ethnic group as the president had about 50 – 150% increase in odds of receiving health aid (46% for 5-mi aid impact zone, 77% for 10-mi aid impact zone, and 153% for 15-mi aid impact zone). While results do not show causation, the results suggest that ethnic patronage could have played a role after the 2009 election. However, Presidential Ethnic Match was associated with receiving less aid in 2010 for purpose and activity-coded aid, which weakens this claim. Nevertheless, further examining ethnic patronage in regards to foreign aid after the 2009 election could be worthwhile. All other years fail to find evidence that Presidential Ethnic Match increased the odds of receiving aid. This provides additional evidence for Dietrich’s (2011) claim that health aid may be spared from political corruption.

Presidential Ethnic Match results also highlight how estimators can be sensitive to the extent of the aid impact zone. In some years only the 15-mi aid impact zone shows preference for Lomwe groups. This indicates that aid projects were located in areas just over 10 mi from a large number of Lomwe people.

5.2 Health Outcomes: Is Foreign Health Aid Important?

Methods

In this section I examine the determinants of aid outcomes, asking which variables influence disease prevalence. Here, the dependent variable is whether a person reported being sick or injured in the two weeks prior to being surveyed. As this is a binary variable, logistic regressions are used. I develop six separate models, where I consider both variations of health aid at the three different aid impact zones. Aid variables now are included as independent variables, and I examine the importance of foreign health aid relative to other variables.

The same AIC modeling approach specified in the precious section is used here. Again, little theory exists for the impact of health aid at the sub-national level, and all combinations of variables could be a justifiable hypothesis. Therefore, utilizing model averaging and allowing all possible combinations of models to model is useful and justified.

The same variables as above are excluded from being in the same model. No worrisome correlations are found between foreign aid variables (see Table 14 in appendix).

Table 4. Determinants of Health Outcomes. *'P Aid' refers to purpose coded aid projects and 'P&A Aid' refers to purpose and activity coded aid projects.*

	Disease Incidence, with aid at the 5 mi aid impact zone		Disease Incidence, with aid at the 10 mi aid impact zone		Disease Incidence, with aid at the 15 mi aid impact zone	
	P Aid	P&A Aid	P Aid	P&A Aid	P Aid	P&A Aid
Distant to Pop. Center	-0.0062 (0.00072) [1]	-0.00488 (0.00064) [1]	-0.0053 (0.0011) [1]	-0.0047 (0.00078) [1]		
Pop. Density					-.0069 (0.0011) [1]	-0.0071 (0.0011) [1]
Presidential Ethnic Match	-0.087 (0.057) [0.86]	-0.078 (0.064) [0.81]	-0.044 (0.075) [0.61]	-0.063 (0.078) [0.72]	-0.085 (0.064) [0.88]	-0.047 (0.081) [0.64]
Health Care Quality	-0.17 (0.020) [1]	-0.16 (0.021) [1]	-0.17 (0.021) [1]	-0.17 (0.012) [1]	-0.18 (0.021) [1]	-0.18 (0.021) [1]
Distance to Health Center	-0.0066 (0.0070) [0.736004209]	-0.0096 (0.0061) [0.88]	-0.0021 (0.0088) [0.38]	-0.0039 (0.012) [0.55]	-0.0013 (0.0071) [0.34]	-0.0035 (0.0078) [0.51]
Wealth Perception	-0.13 (0.014) [1]	-0.14 (0.015) [1]	-0.14 (0.015) [1]	-0.15 (0.0047) [1]	-0.14 (0.014) [1]	-0.14 (0.015) [1]
Before 2008 Health Aid	-0.19 (0.050) [1]	-0.18 (0.052) [1]	-0.051 (0.077) [0.66]	-0.13 (0.10) [0.98]	0.23 (0.027) [1]	0.20 (0.028) [1]
2008 Health Aid	-0.27 (0.035) [1]	-0.26 (0.033) [1]	-0.18 (0.035) [1]	-0.19 (0.11) [1]	-0.0056 (0.041) [0.30]	-0.11 (0.039) [1]
2009 Health Aid	-0.29 (0.063) [1]	-0.12 (0.035) [1]	-0.35 (0.047) [1]	-0.073 (0.083) [0.85]	-0.31 (0.053) [1]	0.021 (0.016) [0.39]
2010 Health Aid	0.0026 (0.022) [0.27]	0.10 (0.034) [0.98]	-0.00048 (0.037) [0.27]	0.020 (-0.050) [0.45]	0.10 (0.027) [1]	0.057 (0.023) [0.76]
Precipitation	-0.0015 (0.0065) [1]	0.0020 (0.0032) [1]	-0.0049 (0.0060) [0.86]	0.0011 (0.0024) [0.91]	-0.0042 (0.0073) [0.71]	0.000055 (0.0052) [0.53]
Precipitation^2	0.000013 (0.0000057) [0.54]	-0.00000088 (0.000019) [0.27]	0.000022 (0.0000074) [0.67]	0.00000038 (0.000020) [0.24]	0.000018 (0.0000020) [0.55]	0.0000013 (0.000010) [0.15]
Temperature	0.078 (0.012) [1]	0.089 (0.012) [1]	0.088 (0.010) [1]	0.088 (0.011) [1]	0.066 (0.012) [1]	0.069 (0.016) [1]
Temperature^2	-0.00018 (0.000033) [1]	-0.00021 (0.000032) [1]	-0.00020 (0.000037) [1]	-0.00021 (0.000037) [1]	-0.00015 (0.000032) [1]	-0.00016 (0.000026) [1]
Intercept	-8.94 (1.38) [1]	-10.21 (1.56) [1]	-9.87 (1.57) [1]	-10.11 (1.66) [1]	-7.89 (1.28) [1]	-8.45 (1.23) [1]
ROC Area	0.5711	0.5699	0.5670	0.5638	0.5667	0.5630
Act. vs Predicted R^2	0.0066	0.0066	0.0060	0.0060	0.0079	0.0073
AIC value	46198	46213	46189	46284	46258	46287

Results

Internal and external validation show models to be extremely poor. External validation shows that the models only explained 0.6 to 0.7 percent of the data. Additionally, ROC values are all < 0.6, which shows the models are not much better than random. Therefore, results should be viewed with caution.

Despite poor models, one useful insight that can be taken is examining which aid impact zone fit the model the best. Internal and external validation offers little insight to comparing models because they differ only slightly. However, AIC values show useful differences between models.[12] Comparing delta AIC values shows that purpose coded aid at the 10-mi aid impact zone performed best, outperforming the 5-mi aid impact zone by deta AIC =9 and the 15-mi zone by delta AIC = 70.[13] Purpose and activity coded aid at the 5-mi aid impact zone performed best, outperforming 10 and 15-mi aid impact zones by delta AIC =70.

Additionally, while the models overall fail at providing a strong prediction of disease prevalence, results do correspond for what would be expected to explain disease prevalence for a number of variables. A 0.1 Celsius increase (and hence theoretically greater risk of malaria) corresponds to 7 – 9% increase in odds of getting sick,
A one unit increase in health care quality (for example, from inadequate to adequate) corresponds to 15 – 16% increase in the odds of getting sick. Additionally, a one-unit

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[12] As opposed to models in other sections, AIC values can be compared here because the dependent variable was the same between models.

[13] Theory does not indicate when one AIC value is significantly different from another. However, when averaging all models within a 95 percent confidence set, generally models within an AIC value of 3 or 4 were averaged together. Therefore, even an AIC value of 9 does show a notable different in model fit. A difference of delta AIC of 70 suggest a strongly improbable model.

increase in wealth perception corresponds to about thirteen percent decreased odds of getting sick.

The Lomwe ethnic group (who are in the same ethnic group as the president) show a slightly less chance of getting sick. Lomwe peoples have 5 – 8% reduction in odds of getting sick relative to the rest of the population. This may help to explain why Lomwe groups were less likely to receive foreign health aid. However, Lomwe groups being slightly better off could suggest forms of political favoritism beyond health aid that improved health outcomes.

Results show foreign health corresponding to lower disease burdens at the 5 – 10-mi aid impact zones in all years before 2010. While results only show correlation, this provides evidence that health aid could have caused reductions in disease burdens. In contrast to this conclusion, at the 15 -mi radius all years but 2008 had instances where health aid was associated with greater disease incidence. However, in terms of AIC values, models with health aid at the 15-mi aid impact zone were the worst models, suggesting greater weight should be given to models with 5 mi and 10-mi aid impact zones. To simplify interpretation, I report odds of getting sick of those who received health aid compared to those who did not receive aid in Table 5. For example, Table 5 shows that those who received purpose coded health aid in 2009 had 26 – 29% reduction in odds of getting sick than those who did not receive aid.

Interestingly, 2010 aid largely appears to be associated with increased health burdens. One explanation for this could be that aid was given to areas with higher disease burdens and aid not having time to have a significant impact. However, allocation models from the previous section show disease prevalence to be a relatively unimportant variable in explaining 2010 aid allocation (having AIC weights mostly below 0.30), which weights against this hypothesis.

Beyond examining estimators, useful insight comes from comparing AIC weights between variables. AIC weights show health care quality and wealth perception to be consistently important, having an AIC weight of one in all models. This makes theoretical sense, as both variables are expected to strongly predict health outcomes. Distance to Health Center is less important in explaining health outcomes, having AIC weights that range from 0.34 to 0.73 (depending on variation of aid an aid impact zone). Temperature consistently has AIC weights of one, showing it to be equally as important as wealth perception and health care quality. Presidential Ethnic Match appears mildly important, having AIC weights ranging from 0.61 to 0.88.

Overall, health aid appears important, frequently having AIC weights of one or near one. This shows that health aid overall is similar in importance to variables like health care quality and wealth perception in explaining disease prevalence. However the relative importance of health aid does vary over years, impact zone, and variation of health aid. 2010 purpose coded aid in particular was one of the least important variables across models, having AIC weights of about 0.27 for five and ten mile aid impact zones. As also suggested by 2010 health aid generally having positive estimators, this suggests that 2010 health aid may not have had sufficient time to impact disease prevalence in 2010.

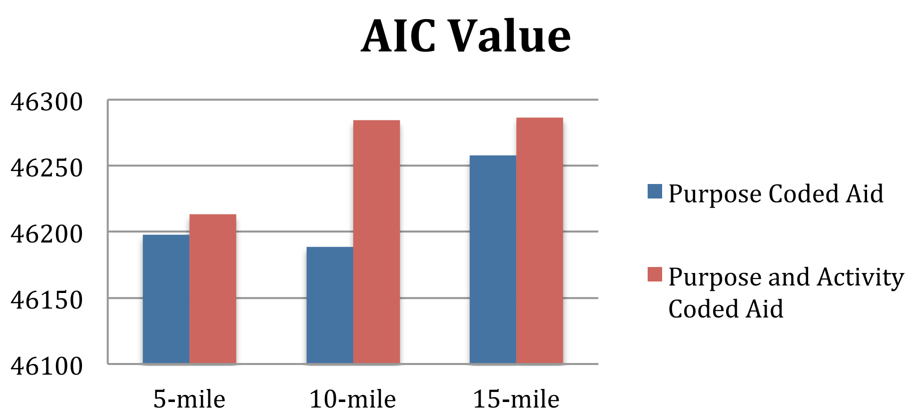
One hypothesis between the two variations of health aid may be that including all aid projects that, in some way, impact health conditions would better explain disease prevalence. However, results do not provide strong evidence for this. In the majority of instances AIC weights between purpose and activity codes are the same. When they are not the same, AIC weights on purpose-coded aid are not consistently higher or lower than purpose and activity coded aid. In some instances the estimator on purpose coded aid is larger than purpose and activity coded aid, while in other cases the opposite is true.

Foreign health aid results do not necessarily show that foreign health aid causes decreases in health outcomes. The causal arrow could also go the other way. For example, negative estimators on health aid variables could suggest higher disease burdens being associated with receiving less aid. Indeed, allocation models from the previous section provide evidence for this, showing that higher disease burdens were largely associated with receiving less aid. Additionally, overall poor models further caution against relying on results in this section. To provide clarification, the next section examines the causal impact of health aid on disease burdens.

Table 5. Odds of getting sick with respect to health aid. *This table reports the odds of getting sick of those who received health aid compared to those who did not receive health aid, controlling for other factors. For an example of interpretation, this table shows that at the 5-mile aid impact zone, the odds of getting sick for those who received purpose coded health aid before 2008 were 18% lower than those who did not receive aid. "P Aid" refers to purpose coded health aid, while "P&A Aid" refers to purpose and activity coded health aid.*

	5-mi aid impact		10-mi aid impact		15-mi aid impact	
	P Aid	P&A Aid	P Aid	P&A Aid	P Aid	P&A Aid
Before 2008	-18%	-16%	-5%	-12%	26%	22%
2008	-23%	-23%	-16%	-18%	-0.6%	-10%
2009	-26%	-11%	-29%	-7%	-27%	2%
2010	0.26%	11%	-0.05%	2%	11%	5%

Figure 8. Model AIC Values.



5.3 Sub-national Aid Impact

Methods

Propensity score matching methods are used to examine causal impacts of treatments when randomized experiments are infeasible. Here, logistic regressions predict assignment to a treatment given a number of covariates, where the predicted value is called the propensity score[14] (Rosenbaum and Rubin 1983). Then, outcomes of treated and untreated individuals with similar propensity scores are compared. In randomized experiments, randomization into control and treatment groups allows treatment affects to be compared because the two groups can be assumed to be similar. Without randomization, direct comparison is misleading because groups exposed to the treatment may differ systematically from the control group due to selection bias. However, propensity score matching overcomes selection bias by comparing individuals with a

[14] The dictionary definition of ‘propensity’ is “a strong natural tendency to do something.” So, the propensity score can be interpreted as a value indicating the natural tendency of being exposed to a treatment. See: Merriam-Webster, "propensity." Last modified 2014. http://www.merriam-webster.com/dictionary/propensity.

similar likelihood of receiving treatment. Here, propensity score matching methods are used to compare disease incidence between individuals with similar propensity scores who do and do not receive foreign health aid for each health aid variable (see Figure 9, which highlights examining the relationship between health aid and disease incidence through controlling for a number of confounding variables). Propensity scores are developed using logistic regressions predicting foreign health aid. An average treatment effect is calculated, which is the reduction in disease prevalence due to health aid.

Propensity scores must be both predictive and have sufficient overlap between treated and untreated groups for matching to occur. To meet these requirements, I use two steps to choose models used to develop propensity scores. First, following the approach in section 5.1 to explain aid allocation, I develop models for all combinations of variables, and rank models according to their AIC value. Second, I select the model where all treated individuals can be matched with untreated individuals, imposing a maximum distance for which propensity scores can be matched. Ensuring sufficient overlap forces the models to be less predictive than the models developed in section 5.1, as some variables are eliminated from the model. However, choosing the best model that meets an established overlap requirement ensures that propensity scores control for the most important variables.

Smith and Todd (2005) and Friedman (2013) highlight how it is difficult a priori to know which maximum distance to compare propensity scores is reasonable, and how generally there is little theoretical guidance in developing propensity scores. Despite this, some literature suggests methods for determining an appropriate maximum distance for propensity scores to be matched. Rosenbaum and Rubin (1985), who developed propensity score matching methods, use a maximum width of 0.25 standard deviations of the propensity scores (Rosenbaum and Rubin 1985; Lunt 2013). However, more recent literature recommends setting the maximum width to 0.2 of the standard deviations of the propensity scores (Austin 2011; Wange et al. 2013). I use the more narrow approach, setting the maximum acceptable distance for propensity scores to be matched to 0.2 of the standard deviation of the propensity scores. The standard deviation of the predicted values of the best model (lowest AIC value) is used to develop the maximum acceptable distance. Once the maximum matching distance is calculated, I choose the best model that meets this overlap requirement. Treated and untreated individuals are matched to minimize the difference in propensity scores. Average treatment affects are reported in Table 6, and final logistic models used to develop propensity scores (with treatment affects and maximum matching distance) are reported in Table 22 in the appendix.

Figure 9. Impact of foreign health aid on disease prevalence, with confounding variables. *Observed difference between foreign health aid and disease prevalence could be due to selection and not the treatment itself. To overcome this selection bias, cofounding factors that influence both health aid and disease are controlled for through propensity score matching.*

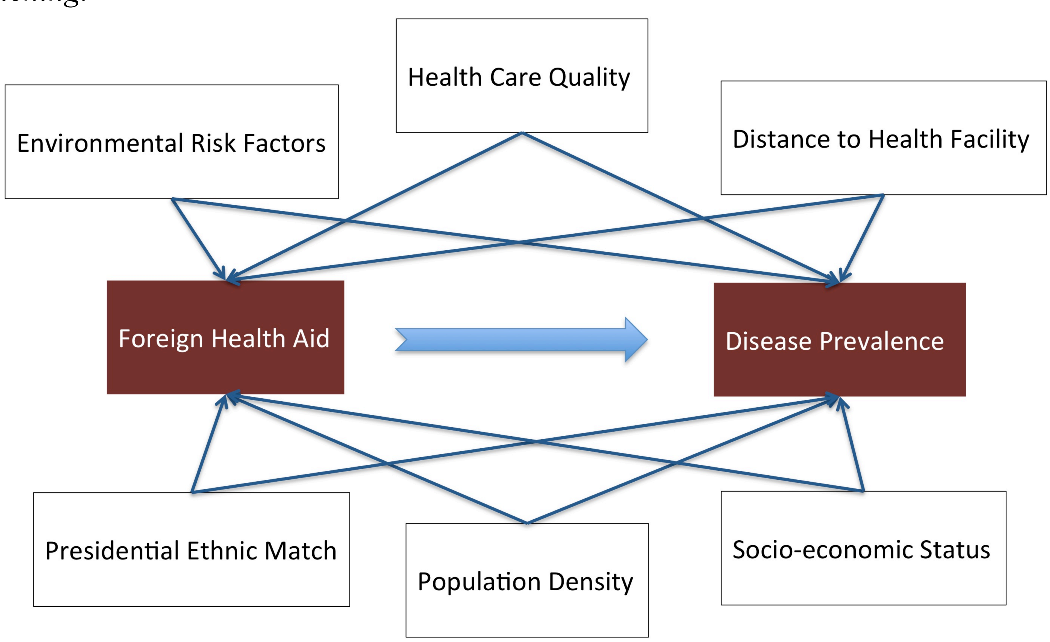


Table 6. Treatment affects of foreign health aid. *Table reports the average causal impact of health on disease incidence. "P Aid" refers to purpose coded health aid, while "P&A Aid" refers to purpose and activity coded health aid.*

	Reduction in Disease Incidence, with 5-mile aid impact zone.		Reduction in Disease Incidence, with 10-mile aid impact zone.		Reduction in Disease Incidence, with 15-mile aid.	
	P Aid	P&A Aid	P Aid	P&A Aid	P Aid	P&A Aid
Before 2008 Health Aid	.041 (.033)	-.005 (.014)	.016 (.035)	.042 (.033)	.020* (.011)	-.010 (.049)
2008 Health Aid	-.024*** (.008)	-.040*** (.007)	-.010 (.007)	-.041*** (.007)	-.018* (.010)	-.090*** (.024)
2009 Health Aid	-.014 (.036)	-.050*** (.012)	-.040*** (.012)	-.041** (.016)	-.026 (.052)	-.026 (.028)
2010 Health Aid	-.003 (.006)	-.028** (.012)	-.010** (.005)	.005 (.007)	-.008 (.006)	-.012 (.008)

Average treatment effects reported, with standard errors reported in parentheses.
* Significant at 10%
** Significant at 5%
*** Significant at 1%

Results

Models appear predictive, despite some variables being removed to allow for sufficient overlap of propensity scores between treated and untreated individuals. R-squared values from regressing actual and predicted values generally are between 0.1 and 0.3, with a range of 0.09 to 0.52. In addition, a number of variables shown to be most important in predicting aid allocation and health outcomes (see sections 5.1 and 5.2) are frequently included in logistic regressions. For example, health care quality, population, poverty/wealth, and environmental risk factors are all included in a majority of the logistic models (see Table 22 in appendix). This gives confidence that confounding variables were sufficiently controlled for, allowing average treatment effect estimates to be trusted.

Results show that foreign health aid has contributed to a statistically significant reduction in disease prevalence since 2008 (using the 95 percent confidence level as the cut-off for statistical significance). However, this impact is sensitive to aid impact zones and the two definitions of health aid. For example, 2008 purpose and activity coded aid significantly reduces disease prevalence with all impact zones, while only 2008 purpose coded aid at the five-mile impact zone exhibits an impact.

Foreign health aid reduced disease burdens by 1 to 9%.[15] Among statistically significant estimates, the average reduction in disease prevalence resulting from foreign aid is four percent. Breaking this down further, the average affect for significant purpose coded aid is 2.5% while the average impact for significant purpose and activity coded aid is 4.6%. This makes theoretical sense, as considering a larger number of aid projects would further reduce disease prevalence if the projects were effective.

The true impact of foreign health aid can be seen from using average treatment effects to estimate the number of incidences of disease reduced and the amount of money it cost for each disease reduction. For example, in 2008, 19,030 people (out of the 50,596 in the sample) were in areas that received purpose coded health aid. A 2.4% reduction in disease prevalence among the 19,030 people in areas that received aid corresponds to 456 people who did not get sick because of foreign health aid. However, extrapolating this estimate to the population and the full year allows a more realistic impact to be seen.[16]

[15] Treatment affects should be interpreted as the difference in disease prevalence between those who received aid and those who did not. As disease prevalence is a binary variable, treatment affects can be interpreted as percentage differences. For example, purpose code aid reducing disease prevalence by "0.024" can be interpreted as health aid reducing disease burdens by 2.4%. In other words, this means that areas that revived health aid had 2.4% lower disease burdens as a result of foreign health aid.

[16] Disease prevalence was measured as the number of people sick in a two-week period. Because foreign aid is considered by aid given in a certain year, more realistic impacts are seen by extrapolating from the two-week period to a year.

The World Bank reports that in 2010 Malawi had a population of 15,013,694. In this year, 37.6% of people where in areas that received purpose-coded health aid, which amounts to 5,646,901 people (World Bank 2014). A 2.4% reduction in disease burdens corresponds to an estimated 143580 less cases of disease as a result of foreign health aid. $21,722,320.23 was spent on health aid, which means that it cost, on average, $151.29 per reduction in disease incidence in the two-week period. Further extrapolating the estimates from the two-week period to a year's time brings the amounts to a reduction of 3,733,080 cases of disease, with an average of $5.82 spent per reduction of illness.[17]

However, some problems could occur from extrapolating to the year's time. The LSMS-ISA makes no mention of the generalizability of the two-week period to a year's time. One particular problem could arise from prevalence of disease changing over the year. For example, malaria transmission increases during the rainy season (November to April). Extrapolating estimates taken from this time period would over-estimate yearly estimates. I check how accurate extrapolating from two-weeks to a year is by estimating the number of malaria cases seen per year in the whole population using the sample LSMS-ISA data and comparing this to the actual number estimated. The survey reported 4383 people having malaria in a two-week period. Extrapolating this to a year would estimate that there were 113,958 cases of malaria among those surveyed in a year. Further extrapolating this to the population means that there was an estimated 30,433,856 cases of malaria per year.[18] However, the President's Malaria Initiative estimates that there are about 8 million cases of malaria per year ("President's Malaria Initiative Malawi: Malaria Operational Plan FY 2013" 2013). Therefore, the survey data

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[17] Calculated by multiplying number of disease incidences reduced by 26, and dividing cost per disease by 26.

[18] Calculated by considering that the survey (55218 people) represents 0.374 percent of the population.

overestimates by a factor of 3.8. To account for this overestimation in reduction in disease incidence, I divide the original estimate for reduction in disease incidence by 3.8 (which then increases cost per disease incidence by a factor of 3.8). Results for all aid estimates that significantly reduced disease burdens at the 95% confidence level are reported in Table 7.

Results estimate that purpose coded health aid prevented 926,249 cases of disease in 2008, 361,803 cases in 2009, and 637,760 cases of disease in 2010. Purpose and activity coded health aid prevented 1.9 million to 5.5 million cases of disease in 2008, 3.5 million to 4.0 million cases of disease in 2009, and 2.3 million cases of disease in 2010. Additionally, results show that the average cost of preventing an incidence of disease was $3.97 to $23.45. These results are generally consistent with estimates of the cost-effectiveness of foreign health interventions. White et al. (2011) review the literature on the costs and cost-effectiveness of malaria interventions, analyzing a total of ninety-eight studies. They find that the median cost of protecting one person against malaria with insecticide-treated nets is $2.20, and protecting with indoor residual spraying is $6.70. Additionally, they find that the average cost of treating an uncomplicated case of malaria is $5.84 and $30.26 for a severe case of malaria.

While results generally show foreign health aid to effectively lower disease burdens, it is important to note that before 2008 aid was not found to be effective, even when it received the most health aid out of all time periods (see Figure 2 in section 3.2). A number of reasons could explain this. First, health aid may simply not have been effective before 2008. Second, the impact of health aid may have had an impact in the immediate years following it, but the affects could have dissipated. Third, problems with the data could cause a failure to find significant impacts. As discussed previously, Malawi's Aid Management Platform was implemented in 2008. While historical data for before 2008 is included, the data is considered incomplete.

Tables 8 and 9 synthesize results from all three empirical analyses, and allow for comparing aid allocation and impact. Results suggest that aid going to those most in need is not necessarily associated with aid having an impact. For example, 2008 purpose coded aid (at the 5-mi aid impact zone) was not allocated effectively according to any variable, except that ethnic preference did not appear to influence allocation. (see Table 8). However, health aid was associated with reducing 926,249 cases of illness. On the other hand, 2010 purpose coded aid (at the 10-mi aid impact zone) reduced nearly 300,000 less cases of illness but was allocated effectively on a number of measures. Here, aid went to those who had worse health care, were at a greater distance from health facilities, were poorer, and who were at a greater risk for disease in terms of temperature.

Purpose and activity coded aid also shows not allocating according to greatest need doesn't prevent aid from having an impact (see Table 9). 2009 purpose and activity coded aid (at the 5-mi aid impact zone) both reduces among the highest cases of disease and is effectively allocated according to five of the eight variables. However, 2010 purpose and activity coded aid (at the 10-mi aid impact zone) reduces 1.7 million less cases of disease than 2009 aid but also is effectively allocated according to five of the eight variables.

In addition, in Tables 8 and 9 I highlight models that best explained disease prevalence from section 5.2 (purpose coded aid at the 10-mi aid impact zone and purpose and activity coded aid at the five-mile impact zone). Impacts from these aid variables can be seen as the best estimates for reduction in disease prevalence due to aid. Generally, aid variables that best explained disease prevalence also showed to effectively reduce disease burdens. From 2008 to 2010, aid variables that best fit that data significantly reduced disease at the 95% confidence level for all but one model (2010 purpose coded aid at the 10-mile radius).

Table 7. Impact of Health Aid

Health Aid Variable	Foreign Health Aid Amounts	Average Treatment Effect (Percent Reduction in Disease Prevalence due to health aid)	Percentage of people in areas that received foreign health aid	Estimated number of people in areas that received aid (% received aid) * (total population)	Amount Spent Per Reduction in Disease in 2-week period	Reduction in disease burden (estimated number of people) * (percentage treatment effect)
					2 week period	
Purpose Coded, 2008, 5-mile radius	$21,722,320	2.4%	37.60%	5,646,901	$160.28	135,526
Purpose Coded, 2009, 10-mile radius	$3,334,305	4%	8.80%	1,323,446	$62.99	52,938
Purpose Coded, 2010, 10-mile radius	$6,679,754	1%	62.20%	933,148	$71.58	93,315
Purpose and Activity Coded, 2008, 5-mile radius	$21,848,912	4%	47.00%	7,051,653	$77.46	282,067
Purpose and Activity Coded, 2008, 10-mile radius	$21,848,912	4.1%	53.00%	7,955,810	$66.98	326,188
Purpose and Activity Coded, 2008,15-mile radius	$21,848,912	9%	60.00%	8,953,142	$27.12	805,783
Purpose and Activity Coded, 2009, 5-mile radius	$29,709,293	5%	78.60%	11,801,815	$50.35	590,091
Purpose and Activity Coded, 2009, 10-mile radius	$29,709,293	4.1%	84.00%	12,614,280	$57.44	517,185
Purpose and Activity Coded, 2010, 5-mile radius	$32,974,913	2.8%	79.80%	11,979,264	$98.31	335,419

Table 7 continued…

Health Aid Variable	Amount Spent Per Reduction in Disease Incidence	Disease reduction	Amount Spent Per Reduction in Disease	Disease reduction
	1 year period		*1 year period, adjusted*	
Purpose Coded, 2008, 5-mile radius	$6.16	3,523,666	$23.45	926,249
Purpose Coded, 2009, 10-mile radius	$2.42	1,376,384	$9.22	361,803
Purpose Coded, 2010, 10-mile radius	$2.75	2,426,185	$10.47	637,760
Purpose and Activity Coded, 2008, 5-mile radius	$2.98	7,333,719	$11.33	1,927,779
Purpose and Activity Coded, 2008, 10-mile radius	$2.58	8,480,893	$9.80	2,229,331
Purpose and Activity Coded, 2008,15-mile radius	$1.04	20,950,352	$3.97	5,507,117
Purpose and Activity Coded, 2009, 5-mile radius	$1.94	15,342,360	$7.37	4,032,972
Purpose and Activity Coded, 2009, 10-mile radius	$2.21	13,446,823	$8.41	3,534,701
Purpose and Activity Coded, 2010, 5-mile radius	$3.78	8,720,904	$14.38	2,292,422

Table 8. Allocation and Effectiveness of Purpose Coded Aid.

	Health Care Quality	Disease Prevalence	Distance to Health Facility	Wealth Perception/ Poverty Level	Pop. Density/ Distance to Pop. Center	Presidential Ethnic Match	Elevation/ Temperature	Precipitation	**Reduced Disease Burden (If Effective)**
Before 2008									
Before 2008 (5m)	-	-	-	-	-	+	-	+	
Before 2008 (10m)	-	.	-	-	-	+	-	+	
Before 2008 (15m)	-	+	-	-	-	-	-	+	
2008									
2008 (5m)	.	-	-	-	-	+	-	-	926,249
2008 (10m)	.	-	-	-	-	+	-	+	
2008 (15m)	+	-	-	-	-	+	-	+	
2009									
2009 (5m)	+	-	-	-	-	+	-	+	
2009 (10m)	+	-	-	-	-	+	-	+	361,803
2009 (15m)	.	-	-	-	-	+	-	+	
2010									
2010 (5m)	+	.	-	+	-	-	+	-	
2010 (10m)	+	.	+	+	-	-	+	-	637,760
2010 (15m)	+	.	-	+	-	-	+	-	

A plus indicates aid going to those most in need, a minus indicates aid going to those less in need, and a period indicates aid relatively unresponsive to that variable (having an AIC weight less than 0.50). I report the estimated number of cases of illness that were prevented due to foreign aid if reductions in foreign aid foreign aid significantly reduced disease burdens at the 95 percent confidence level. Additionally, drawing from results of section 5.2, I highlight aid variables that best explained health disease prevalence (10-mile aid impact zone for purpose coded aid). Pluses are given when aid is associated with: worse health care, higher disease prevalence, greater distance from a health facility, more poor or less wealthy individuals, greater distance from a population center or less population density, not a presidential ethnic match, lower elevations or higher temperatures, and greater precipitation. While 2009 presidential ethnic match for purpose coded aid was omitted from regressions, I denoted it with pluses because it predicted failure perfectly (no individuals in predominantly Lomwe areas received aid).

Table 9. Allocation and Effectiveness of Purpose and Activity Coded Aid

	Health Care Quality	Disease Prevalence	Distance to Health Facility	Wealth Perception/ Poverty Level	Pop. Density/ Distance to Pop. Center	Presidential Ethnic Match	Elevation/ Temperature	Precipitation	**Reduced Disease Burden (If Effective)**
Before 2008									
Before 2008 (5m)	-	.	-	-	-	+	+	+	
Before 2008 (10m)	-	.	-	-	-	+	+	+	
Before 2008 (15m)	-	+	-	-	-	-	+	+	
2008									
2008 (5m)	.	-	-	-	-	+	-	+	1,927,779
2008 (10m)	+	-	-	-	-	+	-	+	2,229,331
2008 (15m)	+	-	-	-	-	+	-	+	5,507,117
2009									
2009 (5m)	+	-	+	+	-	+	+	-	4,032,972
2009 (10m)	.	-	.	+	-	+	+	+	3,534,701
2009 (15m)	-	.	-	+	-	-	+	+	
2010									
2010 (5m)	+	.	+	-	+	+	+	-	2,292,422
2010 (10m)	+	.	+	-	+	+	+	-	
2010 (15m)	+	.	+	-	+	+	+	-	

A plus indicates aid going to those most in need, a minus indicates aid going to those less in need, and a period indicates aid relatively unresponsive to that variable (having an AIC weight less than 0.50). I report the estimated number of cases of illness that were prevented due to foreign aid if reductions in foreign aid foreign aid significantly reduced disease burdens at the 95 percent confidence level. Additionally, drawing from results of section 5.2, I highlight aid variables that best explained health disease prevalence (5-mile aid impact zone for purpose and activity coded aid). Pluses are given when aid is associated with: worse health care, higher disease prevalence, greater distance from a health facility, more poor or less wealthy individuals, greater distance from a population center or less population density, not a presidential ethnic match, lower elevations or higher temperatures, and greater precipitation.

6. DISCUSSION

The main conclusion from this paper is that health aid is found to be effective when analyzing aid at the sub-national level. Logistic models show increases in foreign health aid associated with reduced disease burdens for a number of health aid variables, and propensity score matching methods confirm that health aid causally reduced disease burdens in three of the four time periods considered (2008, 2009, and 2010). Effective health aid is seen despite worries about corruption and poor government capacity to implement programs. This is not to refute donor concerns about inefficiencies involved in foreign aid. However, it highlights that, despite potential inefficiencies, improvements were seen.

Additionally, reduced disease prevalence occurs despite mixed evidence about whether aid was allocated to those most in need. Effective aid was seen even as allocation based on health conditions varied over years, and when, in most years, the poorest individuals were less likely to receive aid compared to others. However, while in some cases aid may go to individuals who are relatively better off than others, these individuals likely still face poor health conditions, as poverty and poor health conditions are pervasive across Malawi. This may result from aid being targeted to areas where it is likely to have the greatest per capita affect rather than targeting aid towards the poorest individuals. Allocation results suggest this could be the case. In most years, more populated areas receive more aid (see Figure 5 and Tables 8 and 9), where poverty rates are lower in urban areas compared to rural areas (Mussa and Pauw 2011). Implementing aid programs in more densely populated areas may mean that aid is more likely to impact a greater number of people for a lower per capita aid amount.

Results contrast with cross-national studies that find that aid does not significantly reduce disease burdens. This discrepancy could be viewed from multiple perspectives. First, Malawi may be an outlier. This paper focused on aid impacts in a single country, while cross-national studies examine average aid impacts across multiple countries. On average, health aid may not have an impact, but aid impacts in Malawi may be above average. Malawi both is among the poorest countries in the world and receives above average per capita aid amounts. Therefore, foreign aid may be uniquely positioned to substantially improve conditions in Malawi. However, sub-national analysis showing foreign health aid to be effective does provide a critique against broad claims from cross-national studies that foreign health aid is ineffective and should not be pursued. Even if health aid might not, on average, have substantial impacts, here results highlight that under certain conditions health aid does have notable aggregate impacts.

Second, contrasting results could suggest that "data deceive" at the macro-level, rather than accurately portraying the effects of health aid. Here, results give evidence against the aggregate impact of health aid being "less the sum of its parts." Aggregate health aid at the sub-national level is found to effectively reduce disease burdens. This is not to say that aid does not have negative effects (such as exacerbating poor governance and reducing government investment in health infrastructure). However, results suggest that the beneficial impacts of health aid outweigh potential negative impacts, at least in terms of directly reducing disease burdens. While sub-national analysis of health aid reveals health aid to be effective, aggregating health outcome and aid amount characteristics to a single number for a country may wash out health aid impacts. Average treatment effects did show aid reducing in the millions of cases of disease;

however, the percentages in disease reduction were relatively small and could explain why impacts may not be picked up on cross-national studies. However, dollar amounts to reduce illness were also small, showing aid to be financially effective and suggesting that greater health aid investment could lead to more substantial impacts. While results cannot show that health aid does drive development, this perspective suggests that health aid can not only "benefit some of the people some of the time," but increased investment in the health sector could promote larger economic growth and "society-wide transformation" (Easterly 2003).

Third, results could be viewed in harmony. Sub-national analysis showing aid to be effective highlights that aid does, as Easterly (2003) argues, "benefit some of the people some of the time;" however, cross-national studies could still be valid in highlighting that aid does not provide a "catalyst for society-wide transformation." Even if aggregate aid can be shown to notably reduce disease burdens at the sub-national level, providing evidence against aggregate negative impacts, health aid could still be limited in promoting vastly improved health conditions. As mentioned before, percentage reductions in disease burdens were relatively small. Other factors may be more important in driving sustained improvements in health and socio-economic conditions. In particular, government investment in health infrastructure strongly determines health conditions. WHO Director General Gro Harlem Brundtland argued that the, "ultimate responsibility for the performance of a country's health system lies with the government." For example, Cuba has low economic resources but strong political resources devoted towards high quality health care, leaving Cuba with low disease burdens (Campion and Morrissey 2013; Drain and Barry 2010; Keck and Reed 2012). Therefore, if health aid does not influence these other barriers, such as quality of governance, it may be limited in its ability to provide “society-wide transformation” in vastly approved health conditions.

This paper provides evidence that health aid, as a whole, can improve health conditions at the sub-national level. However, future research is needed to better understand the extent of the impact of health aid. As discussed in the preceding paragraphs, questions remain about the generalizability of results and the ability for health aid to help drive development. Furthermore, while this paper narrows the analysis from cross-national to sub-national analysis and broadens the perspective from the project-level, further refinement can be made in considering all health aid projects but better examining differences between them. For example, instead of being satisfied with the conclusion that purpose coded health aid projects completed in 2008 reduced disease burdens (for those in districts that received aid and within a 5-mi radius of specifically located aid), we can ask what was it about those projects that made them effective. The analysis says that, collectively, Norway providing aid in the form of medical education and Germany providing aid in the form of basic health care and basic nutrition caused a reduction of an estimated 926,249 cases of disease (Tierney et al 2011). However, further questions can be asked. Are some projects effective while others not, and what makes the effective projects successful? Do projects allow for greater country ownership of improving health outcomes, or do they create dependency on foreign donors? How does sub-national allocation and impact of health aid differ between donor groups— for example, between bilateral and multilateral organizations, and between western and non-western donors? While further refinements can be made, this paper emphasizes the benefits of more closely examining aid impacts, and it cautions against taking insignificant aid impacts found in macro-level studies to mean that health aid should not be pursued.

7. CONCLUSION

The impact of foreign health aid has been an increasingly contested topic as aid flows towards the health sector have increased in the past decades. Scholars examining health aid impacts at the macro-level have largely failed to find significant impacts, while a number of scholars have found notable impacts at the project level. Furthermore, other scholars emphasize the potential of health aid to not only improve health conditions but to help drive development. Contrasting results have fueled debates, but have also led to the emergence of theories that try to explain this apparent ‘micro-macro aid paradox,’ where project-level impacts are seen while macro-level impacts are not. Here, scholars have hypothesized that while specific health projects may have benefits, the aggregate impacts of aid project have negative consequences, ultimately making aggregate impacts not seen.

I utilize new geocoded aid data from Malawi to examine aggregate health aid impacts at the sub-national level. The approach provides a new perspective to examine aid, narrowing cross-national analysis while broadening project-level analysis. In particular, I examine the impact of health aid and how aid is allocated, analyzing how aid responds to socio-economic, health, and political variables. In addition, I ask how allocation might influence the impact of health aid. Similar to broader debates about health aid, the impact of health aid within Malawi is not clear. Some donors highlight that health aid has been beneficial but impacts have been limited due to inefficiencies in the use of aid funds. Corruption and poor governance heighten the chance of minimal aid effectiveness. However, other donors and organizations praise significant impacts of health aid. Therefore, better understanding the aggregate impact of health aid in Malawi is particularly warranted.

I find that aggregate health aid has a statistically significant impact on decreasing health burdens, reducing an estimated 0.3 to 5 million cases of illness per year (depending on year and definition of health aid). Effective aid is seen despite mixed results over aid going to those with the poorest health conditions and aid generally not going to the poorest individuals. Allocations results suggest, though, that aid is allocated to areas with greater populations where it may have a larger per capita impact.

Despite positive impacts seen, results do not help to resolve disputes between those who argue aid is only equipped to “benefit some of the people some of the time,” (Easterly 2003) versus others who argue health aid can catalyze development. However, while results cannot show that there were no inefficiencies or negative consequences of aggregate aid, results do show overall positive impacts despite potential inefficiencies or negative consequences. This gives evidence against scholars who argue that negative impacts of aid may wash out its aggregate impact, at least in terms of health sector aid in Malawi. While questions remain about the role of health aid, results do refute broad claims from macro-level studies that argue that health aid is not beneficial and should not be used. This is nothing new to scholars who examine project level impacts; however, it provides new evidence of health aid effectiveness.

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Appendix

Table 8. Burden of Illnesses for Fifteen Most Prevalent Illnesses[19]

Illness	Number of Cases	Average Days Lost Due to Illness	How much spent on Illness
Fever, Malaria	4383	3.01 (3.30)	78.44 (407.31)
Flu	736	1.71 (2.58)	48.91 (439.85)
Stomach Ache	602	2.61 (3.03)	83.56 (589.67)
Headache	567	2.21 (2.97)	47.66 (280.99)
Lower respiratory (chest, lungs)	504	1.85 (3.11)	56.56 (245.15)
Diarrhea	395	2.29 (2.91)	43.44 (182.82)
Sore Throat	366	2.74 (3.82)	31.61 (122.80)
Upper respiratory (sinuses)	247	2.87 (3.76)	71.82 (324.66)
Wound	240	3.76 (4.15)	79.29 (413.86)
Skin Problems	207	4.05 (4.51)	119.13 (426.68)
Dental Problem	166	3.56 (3.64)	44.91 (169.95)
Backache	147	3.89 (4.18)	99.73 (471.03)
Asthma	145	3.42 (3.61)	60.344 (260.80)
Eye Problem	114	3.52 (4.22)	52.37 (218.16)
Ear/nose/throat problem	78	2.14 (3.00)	10.26 (65.64)

Data from the LSMS-ISA. Standard deviations reported in parentheses.

[19] Money amounts are in Malawi Kwacha. The exchange rate at the end of 2010, when the data was recorded was 1 USD = 152 MK. See: Exchange Rates UK, "US Dollar to Malawi Kwacha (USD MWK) for 31 December 2010 (31/12/2010)." Last modified 2014. http://www.exchangerates.org.uk/USD-MWK-31_12_2010-exchange-rate-history.html.

Table 9. Purpose coded aid by donor.

Donor	Before 2008	2008	2009	2010
US Agency for International Development				$3,047,975
Norwegian Agency for Development Cooperation (NORAD)		$9,764,118	$1,829,181	$3,631,779
Icelandic International Development Agency (ICEIDA)			$1,505,123	
German Agency for International Cooperation (GIZ)		$11,958,202		
KFW Bankengruppe	$4,018,889			
European Union (EU)	$24,785,008			
Total	**$28,803,897**	**$21,722,320**	**$3,334,304**	**$6,679,754**

Data from Aiddata

Table 10. Purpose coded aid by type

Type	Before 2008	2008	2009	2010
Health, combination of general, basic, and population policy/reproductive health purposes			$1,829,181	$3,631,779
Infectious & Parasitic disease control				$3,047,975
Basic health infrastructure	$4,018,889		$1,505,123	
Basic health care		$6,314,358		
Basic nutrition		$5,643,843		
Medical education/training		$9,764,118		
Medical services	$7,338,431			
Health policy and administrative management	$17,446,576			
Total	**$28,803,897**	**$21,722,320**	**$3,334,304**	**$6,679,754**

Data from Aiddata

Table 11. Activity coded aid by donor

Donor	Before 2008	2008	2009	2010
African Development Bank (AfDB)				$18,412,772
Icelandic International Development Agency (ICEIDA)				$3,585,746
Food and Agriculture Organization (FAO)		$126,5920	$412,663	$4,296,640
US Agency for International Development			$13,891,083	
Norwegian Agency for Development Cooperation (NORAD)			$3,333,246	
UK Department for International Development (DfID)			$6,291,428	
Canadian International Development Agency (CIDA)			$2,446,567	
World Bank	$33,826,485			
Total	**$33,826,485**	**$126,592**	**$26,374,988**	**$26,295,158**

Data from Aiddata

Table 12. Activity coded aid by type

Type	Before 2008	2008	2009	2010
Agricultural development			$412,663	$18,412,772
Basic drinking water supply and basic sanitation				$3,585,746
Food aid/Food security programmes			$13,891,083	$4,296,640
Multisector aid			$3,333,246	
Population policies/ programmes and reproductive health, combinations of activities			$6,291,428	
Social/ welfare services		$126592		
Education policy and administrative management	$33,826,485			
Total	**$33,826,485**	**$126,592**	**$23,928,420**	**$26,295,158**

Data from Aiddata

Table 13. Summary Statistics of Variables

	Mean	Std. Dev.	Min	Max
Disease Prevalence	.173094	.3783319	0	1
Distance to Health Facility	4.053472	2.834453	0	22.5465
Health Care Quality	1.755043	.5784383	0	3
Population Density (in hundreds of people).	6.217847	16.78427	0	220.9393
Distance to Population Center	34.8844	22.81616	.11	120.67
Lomwe	.1163151	.3206052	0	1
Wealth Perception	2.064641	.9153578	0	6
Poverty Level	2.62512	1.220955	0	5
Temp	217.313	20.14939	173	264
Precipitation	109.0693	24.97654	75.5	214.2
Elevation	87.13193	35.02636	3.8	174.2

Table 14. Spearman Correlations

	Disease Prevalence	Health Care Quality	Distance to Health Facility	Distance to Pop. Center	Pop. Den	Poverty Level	Wealth Perception	Presidential Ethnic Match	Precipitation	Elevation	Temperature
Disease Prevalence	1										
Health Care Quality	-0.046	1									
Distance to Health Facility	0.015	-0.0695	1								
Distance to Pop. Center	-0.0011	-0.0073	0.26	1							
Pop. Density	-0.0076	0.055	-0.54	-0.45	1						
Poverty Level	-0.059	0.11	-0.13	-0.12	0.13	1					
Wealth Perception	-0.021	0.15	-0.10	-0.079	0.10	0.35	1				
Presidential Ethnic Match	0.0075	0.056	-0.077	0.091	0.18	-0.10	0.036	1			
Precipitation	0.0033	0.096	-0.10	-0.023	0.13	-0.0059	0.055	0.41	1		
Elevation	-0.0096	0.065	-0.045	0.029	0.031	0.039	-0.010	-0.092	-0.14	1	
Temperature	0.0048	-0.056	0.12	0.14	-0.18	-0.053	-0.014	0.0073	0.12	-0.94	1

Table 14 continued…

	Before 2008 Aid (5mi)	2008 Aid (5mi)	2009 Aid (5mi)	2010 Aid (5mi)	Before 2008 Aid (10mi)	2008 Aid (10mi)	2009 Aid (10mi)	2010 Aid (10mi)	Before 2008 Aid (15mi)	2008 Aid (15mi)	2009 Aid (15mi)	2010 Aid (15mi)
B2008 Aid (5mi)	1											
2008 Aid (5mi)	0.44	1										
2009 Aid (5mi)	0.31	0.10	1									
2010 Aid (5mi)	-0.063	0.093	0.22	1								
B2008 Aid (10mi)	0.80	0.41	0.23	-0.10	1							
2008 Aid (10mi)	0.38	0.87	0.075	0.043	0.44	1						
2009 Aid (10mi)	0.25	0.18	0.87	0.25	0.32	0.14	1					
2010 Aid (10mi)	-0.080	0.062	0.21	0.95	-0.12	0.0071	0.24	1				
B2008 Aid (15mi)	0.68	0.44	0.20	-0.091	0.85	0.45	0.28	-0.11	1			
2008 Aid (15mi)	0.36	0.75	0.065	0.0042	0.41	0.85	0.12	-0.033	0.45	1		
2009 Aid (15mi)	0.20	0.23	0.77	0.28	0.27	0.19	0.88	0.27	0.33	0.16	1	
2010 Aid (15mi)	-0.10	0.022	0.20	0.90	-0.15	-0.039	0.22	0.94	-0.14	-0.068	0.25	1
Disease Prevalence	-0.034	-0.040	-0.031	0.0093	-0.020	-0.025	-0.034	0.0099	-0.0047	-0.0098	-0.028	0.014
Health Care Quality	0.083	0.046	-0.0055	-0.10	0.093	0.038	0.0025	-0.0903	0.087	0.020	0.012	-0.086
Distance to Health Facility	-0.38	-0.26	-0.12	-0.0080	-0.40	-0.27	-0.13	-0.0022	-0.35	-0.23	-0.11	-0.014
Distance to Pop. Center	-0.51	-0.54	-0.16	-0.21	-0.57	-0.57	-0.21	-0.1819	-0.59	-0.59	-0.23	-0.14
Pop. Density	0.51	0.39	0.20	0.075	0.53	0.39	0.23	0.089	0.50	0.34	0.19	0.090
Poverty Level	0.19	0.18	0.13	0.0015	0.15	0.17	0.13	-0.018	0.13	0.13	0.13	-0.028
Wealth Perception	0.13	0.12	0.084	0.022	0.10	0.092	0.078	0.026	0.090	0.061	0.080	0.027
Presidential Ethnic Match	-0.056	-0.037	-0.098	-0.062	0.0099	-0.0559	-0.1126	-0.013	0.10	-0.058	-0.12	0.032
Precipitation	0.086	0.13	-0.14	-0.26	0.097	0.14	-0.19	-0.22	0.10	0.14	-0.22	-0.22
Elevation	0.21	0.044	-0.0056	-0.0061	0.22	0.051	0.027	-0.038	0.18	0.041	0.038	-0.076
Temperature	-0.32	-0.14	-0.052	-0.044	-0.35	-0.15	-0.098	-0.026	-0.33	-0.13	-0.11	0.0064

Table 15. Variables.

Variable	Description	Dataset
Disease Incidence	"During the past 2 weeks, have you suffered from an illness or injury?"	LSMS-ISA
Quality of Health Care	"Concerning the standard of health care you receive for household members, which of the following is true? (1 – It was less than adequate for household needs; 2 – It was just adequate for household needs; 3 – It was more than adequate for household needs)."	LSMS-ISA
Distance to Health Center	Euclidian distance from a health facility.	Malawi Spatial Data Portal
Distance to Population Center	Euclidian distance to a population center of over 20,000 people.	LSMS-ISA
Population Density	Population estimates in 1km grids in 2000.	Socioeconomic Data and Applications Center (SEDAC)
Wealth Perception	"Imagine six steps, the first being the poorest people and the sixth the richest. On which step are you today? (1-6)."	LSMS-ISA
Poverty Level	"Which of the following is true? Your current income . . . Allows you to build your savings (1) Allows you to save just a little (2) Only just meets your expenses (3) Is not sufficient, so you need to use your savings to meet expenses (4) Is really not sufficient, so you need to borrow to meet expenses (5)"	LSMS-ISA
Presidential Ethnic Match	Delineates whether an individual was an Enumerated Area that was primarily Lomwe.	Malawi 2008 Census
Temperature	Annual mean temperature	LSMS-ISA
Elevation	Elevation	LSMS-ISA
Precipitation	Annual precipitation (mm)	LSMS-ISA

Descriptions in quotations are direct quotes from the LSMS-ISA survey.

Figure 10. *Spatial distribution of foreign health aid. Health aid defined as aid projects with a health purpose code. Point-location aid is at the 10-mile radius.*

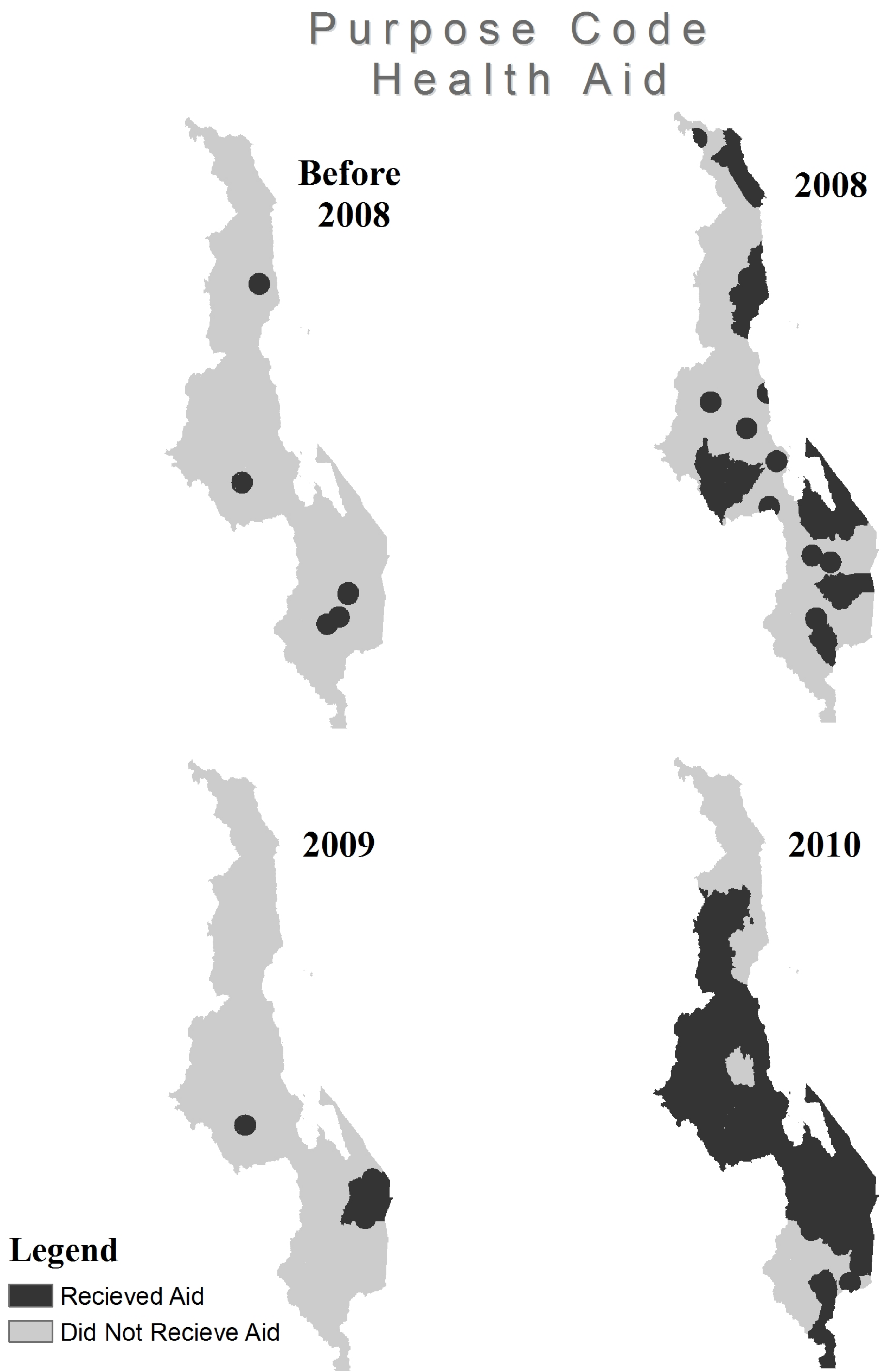

Figure 11. *Spatial distribution of foreign health aid. Health aid defined as aid projects with health purpose and activity codes. Point-location aid is at the 10-mile radius.*

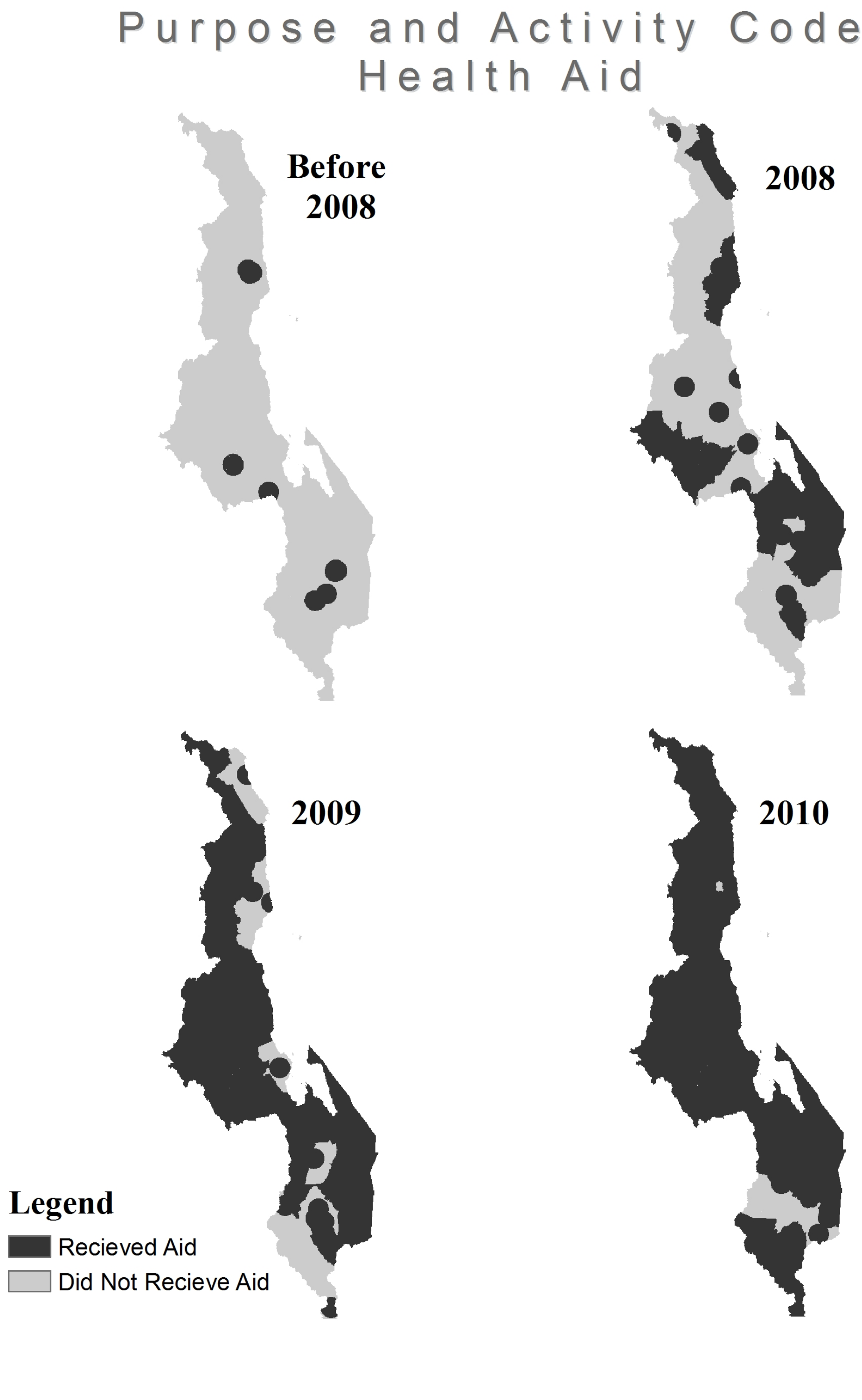

Figure 12. *Location of interviews for LSMS-ISA dataset.*

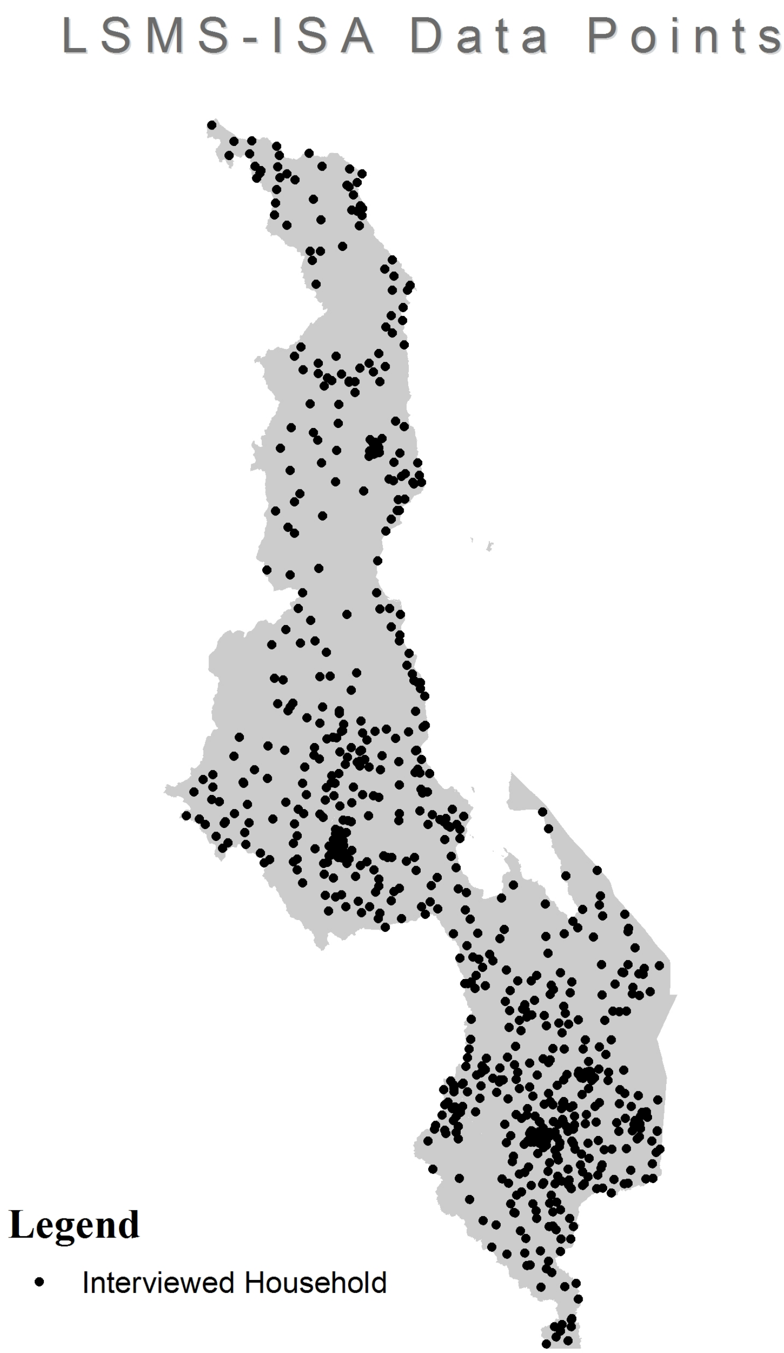

Figure 13. *Location of households that are in a predominantly Lomwe area.*

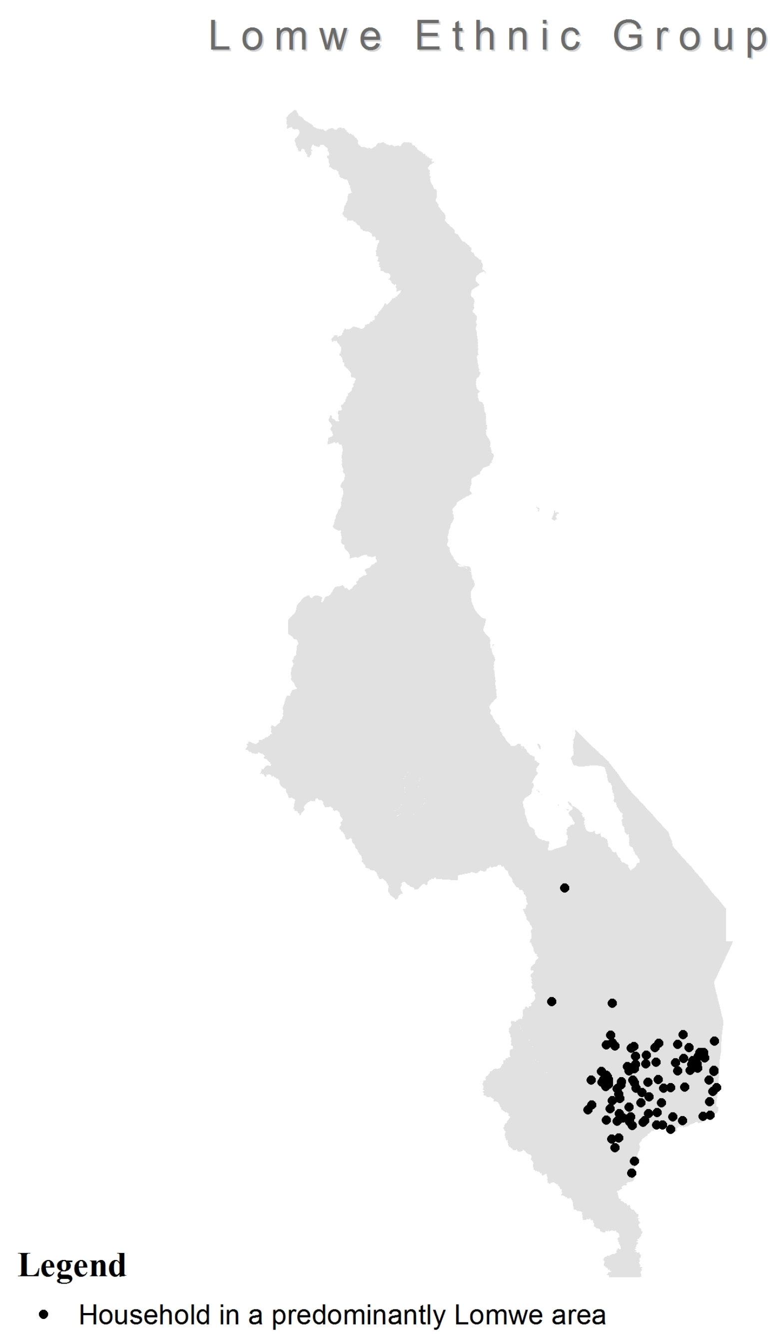

Table 16. Purpose Coded Aid Allocation at the 5-mile Aid Impact Zone

	Foreign Health Aid *Before 2008*	Foreign Health Aid *2008*	Foreign Health Aid *2009*	Foreign Health Aid *2010*
Disease Prevalence	-0.15 (0.060) [0.92]	-0.29 (0.031) [1]	-0.29 (0.057) [1]	-0.0014 (0.0072) [0.27]
Health Care Quality	0.065 (0.033) [0.74]	0.0016 (0.0056) [0.28]	-0.25 (0.037) [1]	-0.38 (0.018) [1]
Distance to Health Facility	-0.34 (0.017) [1]	-0.10 (0.0046) [1]	-0.11 (0.0092) [1]	-0.0055 (0.0027) [0.75]
Population Density			0.025 (0.00081) [1]	
Distance to Population Center	-0.18 (0.0035) [1]	-0.066 (0.00069) [1]		-0.027 (0.00049) [1]
Wealth Perception	0.22 (0.027) [1]	0.34 (0.013) [1]	0.39 (0.020) [1]	
Poverty Level				0.036 (0.0084) [1]
Presidential Ethnic Match	-1.48 (0.085) [1]	-0.71 (0.040) [1]		0.38 (0.035) [1]
Precipitation	0.35 (0.024) [1]	-0.0037 (0.0040) [1]	0.081 (0.024) [1]	-0.12 (0.0035) [1]
Precipitation^2	-0.0014 (0.00011) [1]	0.00011 (0.000015) [1]	-0.00075 (0.00012) [1]	0.00037 (0.000014) [1]
Elevation	0.42 (0.010) [1]	0.052 (0.0019) [1]	0.37 (0.0099) [1]	
Elevation^2	-0.0019 (0.000051) [1]	-0.00024 (0.0000010) [1]	-0.0023 (0.000059) [1]	
Temperature				0.53 (0.010) [1]
Temperature^2				-0.0012 (0.000024) [1]
Intercept	-40.41 (1.45) [1]	-2.06 (0.26) [1]	-16.51 (1.29) [1]	-47.27 (1.10) [1]
ROC Area	0.98	0.86	0.88	0.74
Actual vs Predicted R^2	0.78	0.33	0.18	0.14

Estimator values reported with standard errors in parentheses and AIC weights in brackets

Table 17. Purpose Coded Aid Allocation at the 10-mile Aid Impact Zone

	Foreign Health Aid *Before 2008*	Foreign Health Aid *2008*	Foreign Health Aid *2009*	Foreign Health Aid *2010*
Disease Prevalence	-0.0071 (0.017) [0.29]	-0.21 (0.031) [1]	-0.34 (0.052) [1]	-0.0010 (0.0071) [0.27]
Health Care Quality	0.32 (0.040) [1]	-0.000052 (0.0055) [0.27]	-0.13 (0.033) [1]	-0.31 (0.018) [1]
Distance to Health Facility	-0.34 (0.013) [1]	-0.12 (0.0045) [1]	-0.13 (0.0085) [1]	-0.0029 (0.0019) [0.53]
Distance to Population Center	-0.17 (0.0026) [1]	-0.072 (0.00071) [1]	-0.035 (0.0011) [1]	-0.025 (0.00049) [1]
Wealth Perception		0.30 (0.013) [1]	0.38 (0.019) [1]	
Poverty Level	-0.13 (0.019) [1]			0.041 (0.0084) [1]
Presidential Ethnic Match	-0.73 (0.079) [1]	-1.07 (0.041) [1]		0.57 (0.035) [1]
Precipitation	0.35 (0.016) [1]	0.042 (0.0040) [1]	0.19 (0.025) [1]	-0.14 (0.0034) [1]
Precipitation^2	-0.0013 (0.000070) [1]	-0.000068 (0.000015) [1]	-0.0013 (0.00012) [1]	0.00048 (0.000013) [1]
Elevation	0.50 (0.0090) [1]	0.057 (0.0018) [1]	0.30 (0.0078) [1]	
Elevation^2	-0.0024 (0.000047) [1]	-0.00026 (0.000010) [1]	-0.0018 (0.000046) [1]	
Temperature				0.55 (0.010) [1]
Temperature^2				-0.0012 (0.000024) [1]
Intercept	-43.084 (1.03) [1]	-4.27 (0.26) [1]	-18.87 (1.32) [1]	-47.69 (1.10) [1]
ROC Area	0.98	0.87	0.88	0.73
Actual vs Predicted R^2	0.77	0.36	0.27	0.13

Estimator values reported with standard errors in parentheses and AIC weights in brackets

Table 18. Purpose Coded Aid Allocation at the 15-mile Aid Impact Zone

	Foreign Health Aid *Before 2008*	Foreign Health Aid *2008*	Foreign Health Aid *2009*	Foreign Health Aid *2010*
Disease Prevalence	0.13 (0.047) [1]	-0.11 (0.030) [1]	-0.24 (0.046) [1]	0.0094 (0.0098) [0.37]
Health Care Quality	0.30 (0.031) [1]	-0.024 (0.013) [0.65]	-0.0073 (0.0098) [0.33]	-0.30 (0.018) [1]
Distance to Health Facility	-0.18 (0.0082) [1]	-0.088 (0.0042) [1]	-0.087 (0.0074) [1]	-0.018 (0.0036) [1]
Distance to Population Center	-0.14 (0.0017) [1]	-0.074 (0.00071) [1]	-0.039 (0.00098) [1]	-0.023 (0.00049) [1]
Wealth Perception		0.20 (0.013) [1]	0.33 (0.018) [1]	
Poverty Level	-0.11 (0.015) [1]			0.043 (0.0085) [1]
Presidential Ethnic Match	1.35 (0.065) [1]	-1.22 (0.042) [1]		0.93 (0.036) [1]
Precipitation	0.15 (0.0096) [1]	0.086 (0.0040) [1]	0.23 (0.023) [1]	-0.16 (0.0035) [1]
Precipitation^2	-0.00056 (00041) [1]	-0.00024 (0.000015) [1]	-0.0046 (0.00011) [1]	0.00053 (0.000013) [1]
Elevation	0.33 (0.0056) [1]	0.048 (0.0016) [1]	0.25 (0.0064) [1]	
Elevation^2	-0.0017 (0.000030) [1]	-0.00022 (0.0000093) [1]	-0.0015 (0.000037) [1]	
Temperature				0.53 (0.010) [1]
Temperature^2				-0.0012 (0.000024) [1]
Intercept	-22.91 (0.63) [1]	-5.81 (0.26) [1]	-19.08 (1.22) [1]	-45.12 (1.10) [1]
ROC Area	0.96	0.87	0.87	0.72
Actual vs Predicted R^2	0.70	0.37	0.27	0.13

Estimator values reported with standard errors in parentheses and AIC weights in brackets

Table 19. Purpose and Activity Coded Aid Allocation at the 5-mile Aid Impact Zone

	Foreign Health Aid *Before 2008*	Foreign Health Aid *2008*	Foreign Health Aid *2009*	Foreign Health Aid *2010*
Disease Prevalence	-0.0070 (0.018) [0.28]	-0.29 (0.027) [1]	-0.19 (0.034) [1]	0.00078 (0.0089) [0.27]
Health Care Quality	0.18 (0.043) [1]	-0.0098 (0.0079) [0.44]	-0.078 (0.023) [1]	-0.77 (0.022) [1]
Distance to Health Facility	-0.35 (0.0152) [1]	-0.13 (0.0040) [1]	0.020 (0.0051) [1]	0.074 (0.0052) [1]
Population Density			0.18 (0.0069) [1]	-0.021 (0.00074) [1]
Distance to Population Center	-0.18 (0.0032) [1]	-0.034 (0.00051) [1]		
Wealth Perception	0.16 (0.026) [1]	0.34 (0.012) [1]		0.22 (0.014) [1]
Poverty Level			0.18 (0.011) [1]	
Presidential Ethnic Match	-1.36 (0.088) [1]	-1.49 (0.037) [1]	-0.29 (0.044) [1]	-1.13 (0.039) [1]
Precipitation	0.42 (0.022) [1]	0.064 (0.0035) [1]	-0.045 0.0045) [1]	-0.23 (0.0051) [1]
Precipitation^2	-0.0017 (0.0001) [1]	-0.00019 (0.000014) [1]	0.00014 (0.000017) [1]	8.90 (0.000021) [1]
Elevation		0.080 (0.0018) [1]		-0.043 (0.0024) [1]
Elevation^2		-0.00041 (0.000010) [1]		0.00027 (0.000014) [1]
Temperature	0.86 (0.042) [1]		0.35 (0.017) [1]	
Temperature^2	-0.0023 (0.00010) [1]		-0.00095 (0.000039) [1]	
Intercept	-103.87 (4.71) [1]	-6.85 (0.23) [1]	-26.95 (1.88) [1]	17.70 (0.32) [1]
ROC Area	0.98	0.79	0.86	0.79
Actual vs Predicted R^2	0.78	0.21	0.26	0.15

Estimator values reported with standard errors in parentheses and AIC weights in brackets

Table 20. Purpose and Activity Coded Aid Allocation at the 10-mile Aid Impact Zone

	Foreign Health Aid *Before 2008*	Foreign Health Aid *2008*	Foreign Health Aid *2009*	Foreign Health Aid *2010*
Disease Prevalence	-0.0019 (0.015) [0.27]	-0.23 (0.028) [1]	-0.14 (0.038) [1]	-0.0037 (0.0099) [0.28]
Health Care Quality	0.26 (0.039) [1]	-0.019 (0.012) [0.62]	-0.018 (0.013) [0.49]	-0.77 (0.024) [1]
Distance to Health Facility	-0.32 (0.012) [1]	-0.15 (0.0040) [1]	0.0034 (0.0026) [0.46]	0.085 (0.0056) [1]
Population Density			0.16 (0.0075) [1]	-0.021 (0.00078) [1]
Distance to Population Center	-0.18 (0.0025) [1]	-0.042 (0.00055) [1]		
Wealth Perception		0.32 (0.012) [1]		0.21 (0.015) [1]
Poverty Level	-0.12 (0.018) [1]		0.14 (0.013) [1]	
Presidential Ethnic Match	-0.81 (0.078) [1]	-1.80 (0.040) [1]	-0.53 (0.051) [1]	-1.40 (0.043) [1]
Precipitation	0.46 (0.016) [1]	0.10 (0.0037) [1]	0.033 (0.0049) [1]	-0.42 (0.0075) [1]
Precipitation^2	-0.0018 (0.000069) [1]	-0.00034 (0.000014) [1]	-0.00015 (0.000018) [1]	0.0017 (0.000032) [1]
Elevation		0.084 (0.0018) [1]		-0.051 (0.0027) [1]
Elevation^2		-0.00043 (0.000010) [1]		0.00030 (0.000015) [1]
Temperature	1.47 (0.040) 1]		0.28 (0.021) [1]	
Temperature^2	-0.0037 (0.000096) 1]		-0.00079 (0.000047) [1]	
Intercept	-169.06 (4.45) [1]	-8.72 (0.25) [1]	-22.74 (2.34) [1]	28.63 (0.45) [1]
ROC Area	0.98	0.82	0.87	0.82
Actual vs Predicted R^2	0.77	0.25	0.29	0.21

Estimator values reported with standard errors in parentheses and AIC weights in brackets

Table 21. Purpose and Activity Coded Aid Allocation at the 15-mile Aid Impact Zone

	Foreign Health Aid *Before 2008*	Foreign Health Aid *2008*	Foreign Health Aid *2009*	Foreign Health Aid *2010*
Disease Prevalence	0.11 (0.041) [0.94]	-0.16 (0.028) [1]	-0.015 (0.017) [0.32]	-0.0053 (0.011) [0.29]
Health Care Quality	0.19 (0.029) [1]	-0.069 (0.019) [1]	0.076 (0.031) [0.90]	-0.77 (0.026) [1]
Distance to Health Facility	-0.16 (0.0075) [1]	-0.12 (0.0039) [1]	-0.11 (0.0067) [1]	0.083 (0.0059) [1]
Population Density				-0.023 (0.00086) [1]
Distance to Population Center	-0.14 (0.0016) [1]	-0.046 (0.00057) [1]	-0.026 (0.00094) [1]	
Wealth Perception		0.24 (0.013) [1]		0.23 (0.016) [1]
Poverty Level	-0.097 (0.014) [1]		0.11 (0.017) [1]	
Presidential Ethnic Match	0.83 (0.061) [1]	-1.80 (0.040) [1]	0.39 (0.086) [1]	-1.59 (0.050) [1]
Precipitation	0.16 (0.0085) [1]	0.13 (0.0038) [1]	0.055 (0.0060) [1]	-0.83 (0.014) [1]
Precipitation^2	-0.00056 (0.000035) [1]	-0.00045 (0.000015) [1]	-0.00024 (0.000022) [1]	0.0036 (0.000064) [1]
Elevation		0.072 (0.0016) [1]		-0.077 (0.0032) [1]
Elevation^2		-0.00036 (0.0000091) [1]		0.00042 (0.000017) [1]
Temperature	0.79 (0.026) [1]		0.59 (0.026) [1]	
Temperature^2	-0.0020 (0.000060) [1]		-0.0015 (0.000058) [1]	
Intercept	-84.44 (2.82) [1]	-9.31 (0.25) [1]	-55.42 (2.91) [1]	52.06 (0.80) [1]
ROC Area	0.96	0.83	0.90	0.87
Actual vs Predicted R^2	0.64	0.25	0.42	0.33

Estimator values reported with standard errors in parentheses and AIC weights in brackets

Figure 14. Uncertainty in estimators for purpose coded aid at the 5-mile radius, compared to model AIC values. Estimators reported for top 2305 models.

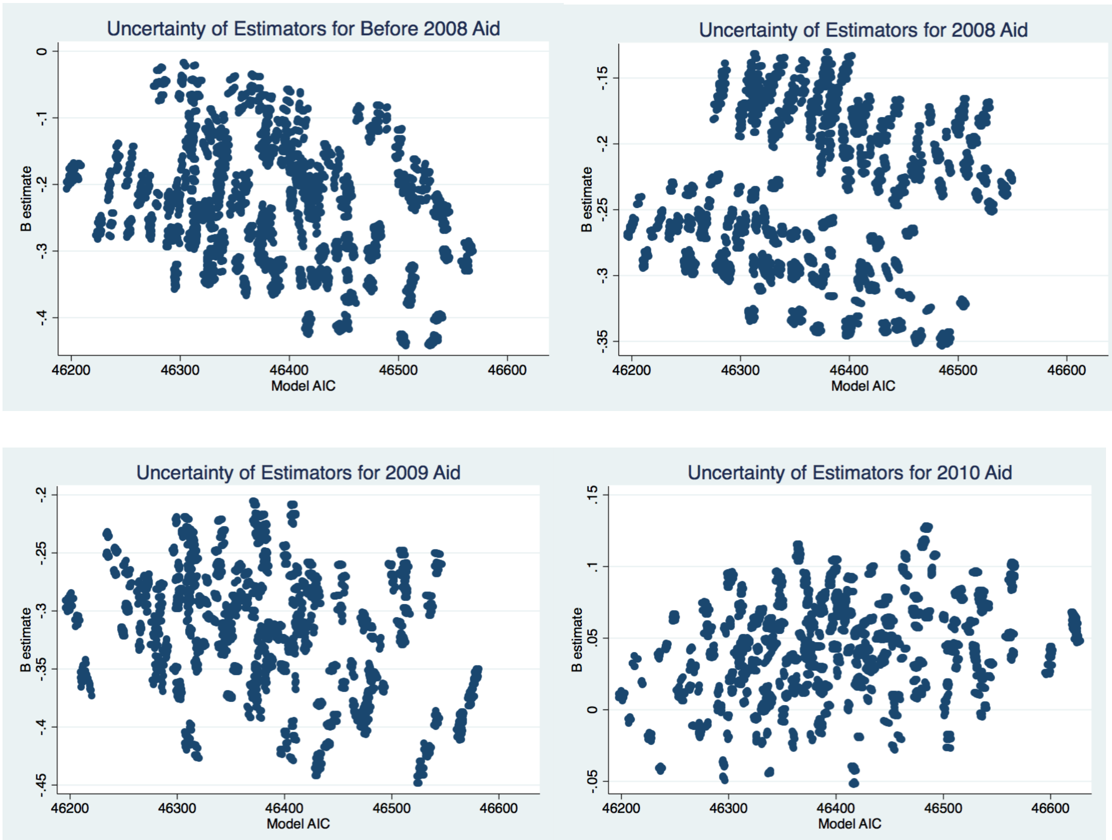

Figure 15. Uncertainty in estimators for purpose and activity coded aid at the 5-mile radius, compared to model AIC values. Estimators reported for top 2305 models.

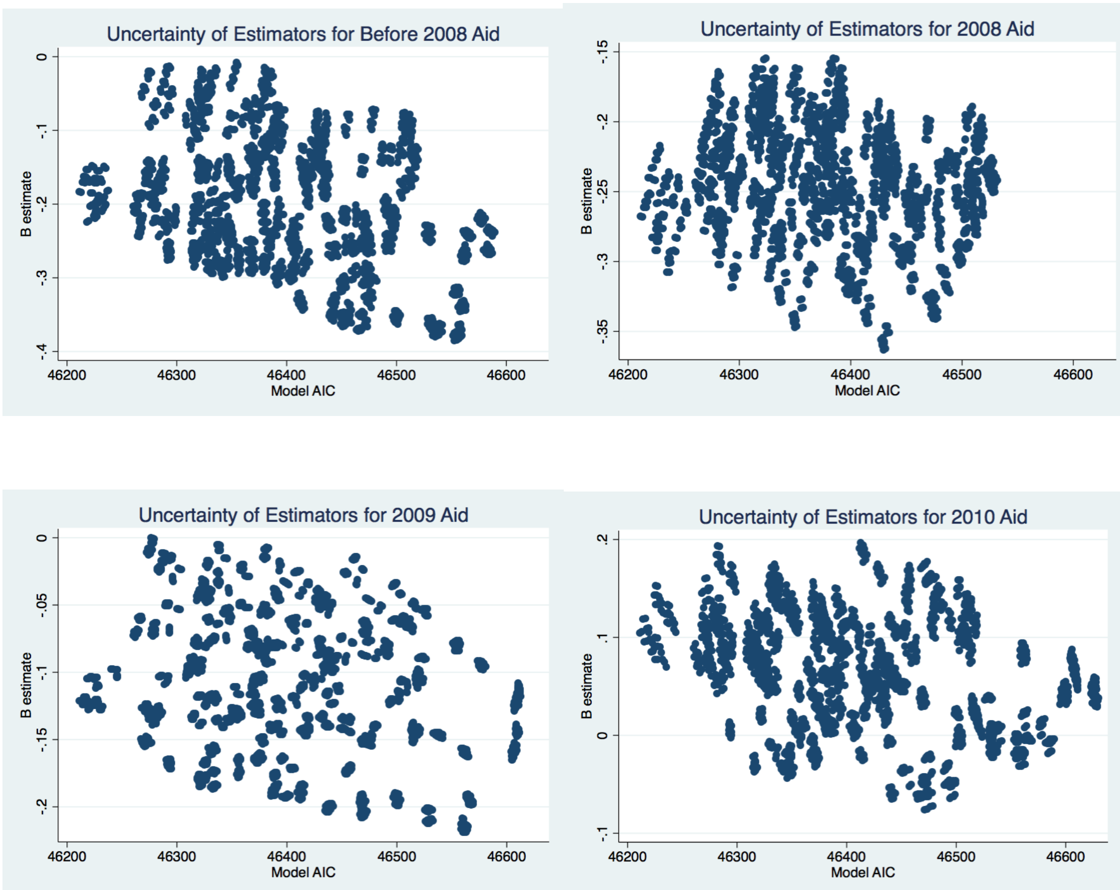

Table 22. *Full Tables of Propensity Matching Method.*

Purpose Codes Aid, 5-mile radius.

	Disease Incidence, *with before 2008 health aid*	Disease Incidence, *with 2008 health aid*	Disease Incidence, *with 2009 health aid*	Disease Incidence, *with 2010 health aid*
Health Aid	0.041 (0.033)	-0.024*** (0.0083)	-0.014 (0.036)	-0.0031 (0.0065)
Logistic Models Used to Develop Propensity Scores				
	Health Aid *Before 2008*	Health Aid *2008*	Health Aid *2009*	Health Aid *2010*
Health Care Quality	0.26*** (0.025)	-0.0032 (0.020)		-0.36*** (0.017)
Distance to Health Facility		-0.090*** (0.0045)	-0.14*** (0.0091)	
Distance to Pop Center		-0.066*** (0.00068)	-0.033*** (0.0010)	-0.022*** (0.00046)
Wealth Perception	0.61*** (0.015)	0.37*** (0.013)	0.41*** (0.019)	-0.021* (0.011)
Presidential Ethnic Match	-0.42*** (0.054)			0.50*** (0.034)
Precipitation		0.020*** (0.00048)	-0.052*** (0.0014)	-0.10*** (0.0034)
Precipitation^2				0.00031*** (0.000013)
Elevation		0.044*** (0.0018)		0.036*** (0.0012)
Elevation^2		-0.00019*** (0.000010)		-0.00022*** (0.0000073)
Temperature	0.48*** (0.026)		1.07*** (0.037)	
Temperature^2	-0.0013*** (0.000062)		-0.0024*** (0.000083)	
Intercept	-46.19*** (2.60)	-3.23*** (0.10)	-113.83*** (3.96)	8.15*** (0.21)
ROC Area	0.82	0.85	0.82	0.72
Actual vs Predicted R^2	0.19	0.32	0.19	0.11
Maximum Propensity Score Matching Distance	0.057	0.059	0.022	0.040

Average treatment affects reported above, with logistic models used to develop propensity scores below. Estimator values are reported with standard errors in parentheses.

* Significant at 10%

** Significant at 5%

*** Significant at 1%

Purpose Codes Aid, 10-mile radius.

	Disease Incidence, *with before 2008 health aid*	Disease Incidence, *with 2008 health aid*	Disease Incidence, *with 2009 health aid*	Disease Incidence, *with 2010 health aid*
Health Aid	0.016 (0.035)	-0.010 (0.0071)	-0.040*** (0.012)	-0.010** (0.0053)
Logistic Models Used to Develop Propensity Scores				
	Before 2008 Health Aid	2008 Health Aid	2009 Health Aid	2010 Health Aid
Health Care Qualiy	0.29*** (0.021)	-0.013 (0.020)	-0.076** (0.030)	-0.31*** (0.017)
Distance to Health Facility		-0.10*** (0.0044)	-0.14*** (0.0082)	-0.0076** (0.0036)
Distance to Pop Center		-0.073*** (0.00071)	-0.039*** (0.0010)	-0.021*** (0.00045)
Wealth Perception	0.42*** (0.013)	0.33*** (0.013)		-0.065*** (0.010)
Poverty Level			0.22*** (0.014)	
Presidential Ethnic Match	0.19*** (0.038)			0.48*** (0.036)
Precipitation		0.010*** (0.0038)	-0.058*** (0.0013)	-0.023*** (0.00047)
Precipitation^2		0.000033** (0.000015)		
Elevation		0.048*** (0.0017)		
Elevation^2		-0.00021*** (0.0000097)		
Temperature	0.62*** (0.022)		-0.0047*** (0.00081)	0.50*** (0.010)
Temperature^2	-0.0016*** (0.000052)			-0.0011*** (0.000023)
Intercept	-61.23*** (2.24)	-1.97*** (0.24)	5.58*** (0.23)	-50.11*** (1.08)
ROC Area	0.79	0.87	0.77	0.71
Actual vs Predicted R^2	0.18	0.35	0.28	0.10
Maximum Propensity Score Matching Distance	0.068	0.063	0.028	0.037

Average treatment affects reported above, with logistic models used to develop propensity scores below. Estimator values are reported with standard errors in parentheses.

* Significant at 10%
** Significant at 5%
*** Significant at 1%

Purpose Codes Aid, 15-mile radius.

	Disease Incidence, *with before 2008 health aid*	Disease Incidence, *with 2008 health aid*	Disease Incidence, *with 2009 health aid*	Disease Incidence, *with 2010 health aid*
Health Aid	0.020* (0.011)	-0.018* (0.010)	-0.026 (0.052)	-0.0083 (0.0058)
Logistic Models Used to Develop Propensity Scores				
	Before 2008 Health Aid	2008 Health Aid	2009 Health Aid	2010 Health Aid
Health Care Quality	0.37*** (0.027)	-0.058*** (0.019)		-0.30*** (0.018)
Distance to Health Facility	-0.27*** (0.0077)	-0.070*** (0.0041)	-0.097*** (0.0071)	-0.020*** (0.0036)
Distance to Pop Center	-0.11*** (0.0012)	-0.074*** (0.00070)	-0.042*** (0.00093)	-0.019*** (0.00046)
Wealth Perception	-0.0058 (0.017)	0.25*** (0.013)		-0.070*** (0.011)
Poverty Level			0.21*** (0.013)	
Presidential Ethnic Match				0.84*** (0.038)
Precipitation		0.051*** (0.0038)	-0.059*** (0.0012)	-0.023*** (0.00047)
Precipitation^2		-0.00013*** (0.000015)		
Elevation		0.039*** (0.0015)		
Elevation^2		-0.00017*** (0.0000090)		
Temperature	-0.049*** (0.00083)		-0.0067*** (0.00074)	0.47*** (0.010)
Temperature^2				-0.0011*** (0.000023)
Intercept	12.24*** (0.19)	-3.31*** (0.24)	6.29*** (0.20)	-47.54*** (1.08)
ROC Area	0.94	0.87	0.78	0.70
Actual vs Predicted R^2	0.52	0.35	0.27	0.094
Maximum Propensity Score Matching Distance	0.070	0.064	0.032	0.036

Average treatment affects reported above, with logistic models used to develop propensity scores below. Estimator values are reported with standard errors in parentheses.

* Significant at 10%
** Significant at 5%
*** Significant at 1%

Purpose and Activity Codes Aid, 5-mile radius.

	Disease Incidence, *with before 2008 health aid*	Disease Incidence, *with 2008 health aid*	Disease Incidence, *with 2009 health aid*	Disease Incidence, *with 2010 health aid*
Health Aid	-0.0049 (0.014)	-0.040*** (0.0068)	-0.050*** (0.012)	-0.028** (0.012)
Logistic Models Used to Develop Propensity Scores				
	Before 2008 Health Aid	2008 Health Aid	2009 Health Aid	2010 Health Aid
Health Care Quality		0.0074 (0.018)	-0.082*** (0.023)	-0.73*** (0.022)
Distance to Health Facility	0.21*** (0.025)	-0.13*** (0.0039)	-0.046*** (0.0047)	0.1193*** (0.0051)
Distance to Pop Center		-0.034*** (0.00051)	0.0063*** (0.00064)	
Wealth Perception				0.14*** (0.013)
Poverty Level	0.37*** (0.012)	0.16*** (0.0086)	0.21*** (0.011)	
Presidential Ethnic Match	-1.054*** (0.055)	-1.58*** (0.037)	-0.37*** (0.043)	-1.065*** (0.038)
Precipitation	0.021*** (0.00069)	0.064*** (0.0035)	-0.0063 (0.0044)	-0.23*** (0.0051)
Precipitation^2		-0.00019*** (0.000014)	-0.0000010 (0.000017)	0.00089*** (0.000020)
Elevation		0.078*** (0.0019)		-0.052*** (0.0025)
Elevation^2		-0.00039*** (0.000010)		0.00030*** (0.000014)
Temperature	-0.074*** (0.0010)		0.21*** (0.017)	
Temperature^2			-0.00062*** (0.000038)	
Intercept	10.20*** (0.20)	-6.64*** (0.23)	-12.96*** (1.89)	17.90*** (0.32)
ROC Area	0.82	0.79	0.85	0.79
Actual vs Predicted R^2	0.19	0.20	0.25	0.13
Maximum Propensity Score Matching Distance	0.059	0.050	0.046	0.035

Average treatment affects reported above, with logistic models used to develop propensity scores below. Estimator values are reported with standard errors in parentheses.

* Significant at 10%

** Significant at 5%

*** Significant at 1%

Purpose and Activity Codes Aid, 10-mile radius.

	Disease Incidence, *with before 2008 health aid*	Disease Incidence, *with 2008 health aid*	Disease Incidence, *with 2009 health aid*	Disease Incidence, *with 2010 health aid*
Health Aid	0.042 0.033	-0.041*** 0.0075	-0.041** 0.016	0.0048 0.0066
Logistic Models Used to Develop Propensity Scores				
	Before 2008 Health Aid	2008 Health Aid	2009 Health Aid	2010 Health Aid
Health Care Quality	0.16*** (0.021)	-0.027 (0.019)		-0.64*** (0.022)
Distance to Health Facility		-0.15*** (0.0040)	-0.035*** (0.0053)	0.13*** (0.0056)
Distance to Pop Center		-0.042*** (0.00055)	-0.0075*** (0.00071)	0.012*** (0.00058)
Wealth Perception	0.41*** 0.013	0.32*** 0.012		
Poverty Level			0.16*** 0.012	
Presidential Ethnic Match	-0.50*** (0.044)	-1.79*** (0.039)	-0.43*** (0.051)	-1.09*** (0.033)
Precipitation	0.019*** (0.00066)	0.10*** (0.0037)	0.045*** (0.0048)	
Precipitation^2		-0.00034*** (0.000014)	-0.00019*** (0.000018)	
Elevation		0.084*** (0.0018)		-0.062*** (0.0026)
Elevation^2		-0.00042*** (0.000010)		0.00034*** (0.000015)
Temperature	0.62*** (0.023)		0.16*** (0.022)	
Temperature^2	-0.0016*** (0.000056)		-0.00054*** (0.000048)	
Intercept	-61.14*** (2.37)	-8.76*** (0.25)	-9.49*** (2.42)	4.54*** (0.12)
ROC Area	0.81	0.82	0.85	0.73
Actual vs Predicted R^2	0.20	0.25	0.29	0.10
Maximum Propensity Score Matching Distance	0.069	0.055	0.041	0.036

Average treatment affects reported above, with logistic models used to develop propensity scores below. Estimator values are reported with standard errors in parentheses.

* Significant at 10%
** Significant at 5%
*** Significant at 1%

Purpose and Activity Codes Aid, 15-mile radius.

	Disease Incidence, *with before 2008 health aid*	Disease Incidence, *with 2008 health aid*	Disease Incidence, *with 2009 health aid*	Disease Incidence, *with 2010 health aid*
Health Aid	-0.0097 (0.049)	-0.089*** (0.024)	-0.027 (0.028)	-0.012 (0.0081)
Logistic Models Used to Develop Propensity Scores				
	Before 2008 Health Aid	2008 Health Aid	2009 Health Aid	2010 Health Aid
Health Care Quality		-0.065*** (0.019)	0.078** (0.034)	-0.61*** (0.022)
Distance to Health Facility	-0.22*** (0.0074)	-0.12*** (0.0039)	-0.11*** (0.0066)	
Distance to Pop Center	-0.13*** (0.0014)	-0.046*** (0.00057)	-0.025*** (0.00093)	0.019*** (0.00060)
Wealth Perception		0.24*** (0.013)		
Poverty Level	-0.026** (0.013)		0.14*** (0.016)	-0.076*** (0.010)
Presidential Ethnic Match	2.53*** (0.051)	-1.8*** (0.040)	0.39*** (0.086)	-0.86*** (0.039)
Precipitation		0.13*** (0.0038)	0.090*** (0.0058)	-0.0015** (0.00063)
Precipitation^2		-0.00045*** (0.000015)	-0.00035*** (0.000022)	
Elevation	0.034*** (0.00055)	0.072*** (0.0016)		-0.086*** (0.0031)
Elevation^2		-0.00036*** (0.0000091)		0.00044*** (0.000017)
Temperature			-0.10*** (0.0015)	
Intercept	-0.32*** (0.066)	-9.35*** (0.24)	22.07*** (0.58)	6.44*** (0.16)
ROC Area	0.94	0.82	0.89	0.72
Actual vs Predicted R^2	0.56	0.25	0.45	0.11
Maximum Propensity Score Matching Distance	0.071	0.054	0.038	0.039

Average treatment affects reported above, with logistic models used to develop propensity scores below. Estimator values are reported with standard errors in parentheses.

* Significant at 10%
** Significant at 5%
*** Significant at 1%